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Doctoral Thesis

Buyer-Seller Relations, Prices and Development: A Structural Approach Exploring the Garment Sector in Bangladesh

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Declaration of Authorship

I, Julia Cajal Grossi, declare that this thesis titled, 'Buyer-Seller Relations, Prices and Development: A Structural Approach Exploring the Garment Sector in Bangladesh' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help (Please, see Appendix K with details on specific contributions to this thesis).
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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Abstract

Department of Economics

Doctor of Philosophy

Buyer-Seller Relations, Prices and Development: A Structural Approach Exploring the Garment Sector in Bangladesh

by Julia CAJAL GROSSI

This thesis aims at understanding how manufacturers' heterogeneity affects the configuration of trading relations and prices in a dynamic environment. The institutional context I study is that of the Ready Made Garment sector in Bangladesh over the 2005 - 2012 period. The research here represents a contribution to that goal in four dimensions. *First*, accessing customs records we constructed a dataset containing buyer - seller trade interactions at a disaggregated level, including volumes and unit prices of the traded goods and, for a subsample, prices and quantities of the inputs required for manufacturing them. This feature allows us to go a step further than most studies based on matched importer - exporter data and opens a fruitful research agenda. *Second*, using this dataset I offer a first characterisation of the dynamics of the relations between manufacturers and large international buyers in matters of (i) duration of the relations, (ii) evolution of volumes, prices, orders and profitability over time, (iii) heterogeneity of the manufacturers and (iv) the probability of trading links arising. I find that relations with large buyers tend to be exclusive, that higher prices are associated with longer lasting relations, which tend to grow over time and fail whenever the manufacturer starts dealing with another large player. Importantly, I present a characterisation of suppliers heterogeneity novel in the literature and show evidence on two salient facts: the higher the heterogeneity across suppliers faced by a buyer, the more persistent its relations are and the higher the markup the buyer is willing to pay .*Third*, I develop a dynamic discrete choice game of linking and bargaining that realises those patterns in the data. I implement an algorithm that computes Markov Perfect Equilibria to discuss aspects of computation, convergence and multiple equilibria in the game and I scan a large parameter space to characterise the mechanisms that drive the dynamics in the industry. *Fourth*, I present the structural approach developed by Lee and Fong (2013) for estimating network formation games with endogenous bargaining and discuss three aspects in which its application is not immediate in my setting. These are related to (i) the availability of prices in our data, (ii) the difficulties in recovering conditional choice probabilities from the data, and (iii) the construction of the distance score. These difficulties lead to a pseudo Monte Carlo exercise that compares (sixteen) alternative estimation procedures. This preliminary study suggests that restricting the objective function to the observed states, using an auxiliary parametric assumption on the conditional choice probabilities in unobserved states and exploiting the data on prices could be fertile paths to explore towards adapting Lee and Fong's approach to estimate structurally the parameters of my game with the data we constructed.

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I express my most heartfelt gratitude to my supervisors, Christopher Woodruff and Gregory Crawford. It has been my privilege to work with them and without their invaluable guidance this PhD would have not been achievable. I cannot thank them enough for their patience, inspiration and advice.

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The Economics Department at Warwick has been a fantastic environment to embark myself on this project and I am grateful to the Head of the Department, Abhinay Muthoo, the Faculty and Support Staff for making of this an outsanding experience.

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Finally, words are short to express my gratitude to my family for teaching me everything I needed to know to get here. It is to them that I would like to dedicate this thesis.

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Chapter 1

Introduction

This thesis is about understanding the mechanisms that drive inter-firm relations in developing countries and, as such, falls between the fields of Industrial Organisation and Development Economics. This ambition constitutes a long run research agenda towards which the studies presented here are my first contributions.

There are three general questions I deal with in this thesis. First, *how are export-oriented manufacturers in developing countries selected into sustained trade with large international buyers?*. Second, *what is the role of manufacturers' heterogeneity and other frictions in the selection process?*. Third, *how are the gains from trade appropriated at each end of these relationships?*. These being empirical questions, two operational goals were in order: to construct a dataset detailed enough to shed light over relatively undocumented features of buyer - seller relations and to adapt or construct a suitable econometric approach to answer those questions.

Of this research plan, the thesis covers the construction of such a dataset, the description of the most salient dynamic aspects of buyer - seller relations, the development of a game-theoretic model in the tradition of the structural Industrial Organisation (IO) literature that realises those dynamics and a first evaluation of structural techniques to estimate this game with our data.

All the empirical work in this thesis looks at the Ready Made Garment (RMG) sector in Bangladesh. I will exploit a unique dataset recording all the trade interactions between exporters in Bangladesh and international buyers, between 2005 and 2012, with a considerable degree of disaggregation[1]. The setting, with regards to the industry and country, is well suited for the purpose of addressing the research questions described above for at least three reasons.

[1]Access to this data is framed in a larger Project under the direction of Prof. Woodruff and Prof. Macchiavello. I gratefully acknowledge their permission to use this data as part of my doctoral research.

First, the dimension of the sector relative to the country's economy and its potential as a driving force for development makes the RMG sector in Bangladesh worthwhile studying in its own right. Bangladesh is possibly one of the leading examples of export-led takeoffs of Low Income Countries in the last couple of decades. Each country with its specificities, these experiences have either one or multiple industrial sectors as the backbone of growth processes tied to an expansion in international trade. The demand from the major consumers of RMG, Europe and US, has grown sharply in the last ten years (see graphs C.1 and C.6 in Appendix C) pulling from the exports of the world's largest suppliers. This process has pushed Bangladesh into the status of second largest exporter of RMG in the world, after China. This, in turn, has translated into an increase in the number of garment factories, which has grown from 830 in 1990 to 5,600 in 2013, and a sharp expansion of employment in garment plants, from 0.4 million workers to 4 million workers over the same period (BGMEA). This figure represents more than 45% of the employment in the industrial sector and exported values in garment account for approximately 82% of all the exports in the country. Together with the increase in the international demand, relatively low wages and fiscal incentives driving the costs of imported inputs down have aided this expansion. A policy review included in Appendix E offers a *racconto* of the governmental and non-governmental policy efforts in this direction.

Second, most of the empirical analysis in this thesis will focus in woven garments. For this category of products, technologies are known to be relatively homogeneous, across products and across firms, which will contribute to interpreting some of our results. Similarly, the majority of the fabric required for producing woven garments is imported. This will allow us to exploit data we have available on imports from garment manufacturers to infer input costs.

Third, when focussing in woven products, we can identify a small number of *large* buyers that every year account for 40 to 50% of the demand for the main woven products in Bangladesh. The size of these players, relative to that of their 5,000+ smaller counterparts, allows us to work at the level of inter-firm relations in depth in a framework of imperfect competition. Statistics at the firm level for large and non-large buyers are presented in tables C.14 to C.42 in Appendix C and a qualitative description of each of these large players is included in Appendix J.

In this context, the **first output** of the research work contained in this thesis was the construction of a dataset with features that, to the best of my knowledge, make it unique. The primary source of our data is the compilation of mandatory export and import records in the main Custom Stations in Bangladesh, between 2005 and 2012. Each record constitutes a product (Harmonised Codes disaggregated to the sixth digit) within a shipment from a supplier to a buyer, taking place on a given date. These are *real-time* records and include details on the statistical values, quantities, destinations and specifics of the terms of trade. Importantly, they include identifiers for all buyers and sellers. The format and conditions in which this data was obtained required a large investment in cross-checking the data with other official sources of information, unification of the records identifying firms uniquely and further robustness and quality controls. The work done on this is documented in Appendices A and B. Although other studies have exploited custom-based data with similar levels of disaggregation, our dataset allows us to go one step further than previous empirical studies on interfirm relations: for a subsample of the data, we can trace back the imported material inputs required for manufacturing the garments fulfilling specific export orders. For each record in this subsample of the exports data, we can identify who the buyer and the seller are, link all the shipments that correspond to the same export order and characterise these flows in terms of volumes and prices of output and inputs (mainly fabric). The details on the matching procedure, assumptions and coverage are included in Appendix D.

We have not found so far precedents of a dataset containing information on input-output matches, with the level of disaggregation of our data and with its extensive coverage. We believe that the scope of questions that can be re-visited using this newly available data is extensive. In this thesis I only explore a small set of aspects relevant to the questions described above. By the time of this submission, there are two streams of ongoing work in which I am involved, closely related to the research reported in this thesis. The first one corresponds to joint research with Christopher Woodruff, Guillermo Noguera and Rocco Macchiavello, on heterogeneity, value addition and upgrading[2]. The second one focusses on heterogeneity and network changes after mergers and acquisitions. These two topics are then excluded from what I report here and constitute examples of what we believe is the potential of this dataset for advancing fruitfully in a research agenda.

The **second contribution** in this thesis is mainly contained in Chapter 2. Here I characterise the relations between large buyers and RMG manufacturers. This part of the thesis is related to recent contributions, mainly in the Trade literature, that use exporter - importer matched data to study different aspects of inter - firm relations: survival and search (Eaton et al., 2014), switching costs (Monarch, 2013), reputation on quality (Macchiavello, 2010), trade intermediation (Blum et al., 2010) buyer and seller heterogeneity (Bernard et al., 2014; Carballo et al., 2013) and (geographic) neighbour externalities (Kamal and Sundaram, 2013), among others.

[2] Institutional affiliations and contact details can be found in *http://www2.warwick.ac.uk/fac/soc/economics/staff/*.

I am able to use the data at the level of the orders to offer a reduced form characterisation of (large) buyer - seller relations on (i) the patterns of survival and duration of relations, (ii) the general time trends in volumes, prices, order allocation, inputs and profitability over the duration of relations, (iii) aspects of firm-level heterogeneity and (iv) network or link formation. The empirical regularities that are found in this analysis show that both the intensity of trade and prices are positively related to the duration of the relation. Opposite to the papers documenting that switches of suppliers are induced by the search for lower prices (for example, Monarch (2013)), I find that manufacturers that are paid higher prices during the first year of the relation are more likely to sustain the relation onto a second year. The evidence I present also shows a picture of highly persistent relations of almost exclusive dealing, where links with large buyers break with a high probability whenever the supplier starts trading with another large player. For established relations, I observe that traded volumes grow over time, induced by the allocation of a higher number of orders from the buyer to the supplier.

The analysis in Chapter 2 offers three contributions. First, exploiting an econometric approach *imported* from the literature in Labour Economics, I offer a simple way of characterising exporters' heterogeneity moving away from the paths that related papers have chosen: estimating firm-level productivity, eventually, via a structural model or assuming that the relevant dimension of heterogeneity is monotonically related to an observable characteristic that can proxy it, in general, exported volumes. The approach here recovers exporters' *types* under relatively mild assumptions with a simple procedure. Second, constructing a measure of heterogeneity, I document a novel fact on buyer - seller relations: in the presence of high heterogeneity across potential unknown sellers, a buyer allocates orders more frequently to his existing suppliers, relative to market conditions in which the heterogeneity of the alternatives is lower. While this is compatible with a number of existing theoretical models, the results presented here constitute, to my knowledge, the first empirical collection of evidence of this type. Third, exploiting a unique feature of our dataset, I find evidence of the existence of a 'premimum' for heterogeneity in the price - cost margins buyers afford. Again, without imposing the restrictions of a specific bargaining protocol, I show evidence indicating that markups in garment orders go up when the heterogeneity the buyer is facing in its outside option is high.

The stylised facts in Chapter 2 lead to the construction of a model that constitutes the **third contribution** of the thesis. In Chapter 3 I develop a dynamic discrete choice game of linking and price setting. The game follows the general structure proposed in Lee and Fong (2013) for studying Markov Perfect Equilibria in network formation games with endogenous bargaining. The model I present has three features compatible with the reduced form evidence found in Chapter 2: first, buyers choose manufacturers competing with each other for suppliers of heterogeneous types; second, buyers pay a sunk cost for forming a relation; third, surplus sharing rules vary with different large buyers.

In simple terms, the game 'starts' with all buyers simultaneously choosing one supplier from a list of available manufacturers by comparing partner-specific inter-temporal profits. The profits derived under each possible choice depend on the cost of forming links, a match-specific component, the future realisations of the network and the prices that the buyer would pay under each configuration of the network. These prices depend non-trivially on the choices of other buyers: the seller's outside option is determined by the offers it can obtain from other buyers that have chosen it as potential supplier. The seller, capacity constrained, will only be able to produce for one of the buyers at most.

The interaction between (i) heterogeneity at the matching level, (ii) sunk costs of forming a link and (iii) competition between buyers determine the *architecture* of the network of trade and its prices. The more formal aspects of the game build directly on the work by Lee and Fong (2013) and are therefore related to Ericson and Pakes's framework to study industry dynamics (1995). Most of the assumptions in the construction of the model are based on well established contributions in structural industrial organisation and present, notably but not exclusively, in Aguirregabiria and Mira (2002, 2007); Doraszelski and Pakes (2007); Doraszelski and Satterthwaite (2010); Hotz and Miller (1993); Pakes and McGuire (1994); Rust (1994).

Among the various papers that propose dynamic oligopoly models, the specifics of my setting make the game similar to those in structural papers that need to *nest* the computation of the stage profits inside of the dynamic programming problem defined by the corresponding value functions (Benkard, 2004; Markovich and Moenius, 2008). In particular, analysing industry dynamics in the light of *networked* strategic interactions, my framework is related to the work by Aguirregabiria and Ho on the US airline industry (2010; 2012).

The bargaining aspect of the game is related to the work by Dranove et al. (2011), whose theoretical construction follows Stole and Zweibel (1996). The distinctive feature of my game is that the evaluation of disagreement points accounts for the effects of disagreement in current negotiations and the future realisations of the network. Lee and Fong's setting accommodates this possibility and a small game with a static example is presented in Appendix H.

The final sections of Chapter 3 implement for the first time Lee and Fong's algorithm to compute Markov Perfect Equilibria of the proposed game, repeatedly over a fine grid of parameters. This allows me to discuss issues around convergence, computation costs and multiplicity. The final remarks in this chapter emphasise the mechanisms that induce the empirical observations in the institutional environment I study[3].

The **fourth outcome** of my research is reported in Chapter 4 of this thesis. The game theoretic model presented in Chapter 3 offers the structure needed for 'recovering' the parameters that characterise the salient facts documented in Chapter 2 on inter-firm relations in the RMG sector in Bangladesh. The dataset available to us contains information on the two relevant market outcomes: who trades with whom at each point in time, and what the price in each of these interactions is. Observing input costs helps construct measures for the value of each relation free from generalising assumptions on the cost side.

The formalisation in Chapter 3 suggests three sets of parameters in the model: a scalar containing the sunk cost of linking, a vector of bargaining parameters (one entry for each buyer) and a matrix containing a match-specific quality (one entry per potential pair). Chapter 4, in this preliminary version of my structural work, treats the matching-qualities as observed and reduces the parameter set to the cost of linking and the bargaining powers. This restriction simplifies the analysis in this chapter and is left to be relaxed at a later stage, when a more systematic discussion on identification is presented and the challenges described below are sorted.

This final chapter, therefore, studies the two-step procedure proposed in Lee and Fong (2013), building on the work by Bajari et al. (2007), to recover the parameters that realise the equilibrium observed in our data, expressed in active trade and observed prices. I first present a number of operational assumptions required for estimating the game in Chapter 3 using our data. I then discuss three aspects in which my setting imposes challenges to the applicability of the structural approach developed by Lee and Fong. The first of these is the availability of prices in our data. Second, the difficulties in the non-parametric estimation of conditional choice probabilities from the data when the state space is large and choices are highly persistent. Third, and related to the previous point, the construction of the distance score adding over states that have no instances observed in the data. This discussion leads to a pseudo Monte Carlo exercise that compares (sixteen) alternative estimation procedures.

The overall estimation procedure uses forward simulation as in Bajari et al. (2007) to obtain value functions. Following Lee and Fong, a prices-to-values fixed point routine is performed to generate prices consistent with those values. I explore the possibilities of (i) generating all prices in the system and (ii) excluding from the fixed-point routine

[3]All the Matlab code producing the results for this section are available upon request for the examiners' evaluation.

the prices observed in the data, that would then act as 'constraints' in the iterative procedure that solves the simultaneous Nash problems. The second stage of the estimation finds the optimal policies for each player and computes the conditional choice probabilities that would arise under alternative candidate parameters in the equilibrium play. These probabilities are compared with those estimated directly from the data. I explore different alternatives for this step, using the 'true' underlying probabilities in the simulated data as a baseline. These alternatives are: (i) using a standard non-parametric frequency estimator with a kernel to approximate probabilities in the unobserved bins of the conditional transitions, (ii) assuming that the choice probabilities in unobserved states coincide with the observed unconditional probabilities and (iii) attaching equal probability to all actions being chosen by the players in unobserved states. Finally, I look at constructing the distance score (which in this setting is the objective function in the minimisation problem that searches for the estimates of the parameters) using all the states of the world and only adding up over observed states.

The small exercise performed in this chapter shows some evidence implying that restricting the objective function to the observed states, using an auxiliary parametric assumption on the conditional choice probabilities in unobserved states and exploiting the data on prices could be fertile paths to explore towards constructing a more suitable econometric approach. The validity of these ideas needs to be corroborated with a more extensive Monte Carlo procedure, which is the matter of my current research.

Chapter 2

Buyer-Seller Relations in the Ready Made Garment Sector in Bangladesh

2.1 Introduction

It is a well documented fact that contracts between buyers and sellers in export markets are often incomplete and ensuring the quality and timely delivery of orders tends to be a major concern for international buyers (see Monarch (2013), Macchiavello (2010) , for example). Depending on the market, the underlying uncertainty is usually connected to the quality of the goods, the reliability of the seller (in terms of lead times, for example) and / or her productivity in a broader sense. While some of these can successfully be tested and assessed within the course of a trading relationship, ex-ante, there is some incompleteness in what buyers know about their suppliers. In particular, the garment sector in Bangladesh is unfortunately famous for its lack of compliance with minimum health and safety requirements and human rights, even when firms hold all the necessary credentials. Governmental and official controls for these are known to be very weak, and episodes of extensive coverage in the media have proved the difficulties buyers face, even after engaging in costly screening processes, to identify out suppliers that might secretly break their compliance agreements. [1]

[1]The tragedy in Savar in April 2013 had 1,100 people killed, after they were locked inside a collapsing building. The facilities involved factories that were producing orders for large buyers like Primark, Benetton and Walmart. The media has reported several (smaller) cases in which manufacturers serving large buyers experienced explosions, fires, sexual harassment accusations, forced overwork, illegal subcontracting, etc.. Only in 2006, large buyers like Inditex-Zara, Carrefour, Kmart, H&M and PVH were involved in 14 episodes of these kinds. These episodes have proven costly for the buyers in that, first, they needed to put in place compensation schemes in occasions and, second, (and most importantly), they needed to deal with media scandals potentially damaging to their reputation.

Data (un)availability and the elusiveness of the object have made the collection of empirical evidence on the relation between such uncertainty and micro - level decisions in trade almost impossible. The recent (and growing) availability of disaggregated matched exporter - importer datasets has opened the possibility of revising a number of relevant questions related to the one addressed here. Relevant contributions to this growing literature include Eaton et al. (2014), who show evidence on survival patterns in a panel of exports between US buyers and Colombian firms, supporting a model of trade with search on the sellers' side. Monarch (2013) exploits a matched dataset of trade between Chinese manufacturers and US buyers to describe a setting in which buyers switch suppliers in search of lower prices. Macchiavello (2010) studies the process of building a reputation on quality in relations between wine makers in Chile and their distributors. Within the trade modelling literature, a number of papers have also exploited matched exporter-importer data to study trade intermediation, notably Blum et al. (2010) and subsequent papers by the same authors (Blum et al., 2009). With specific attention to buyer and seller heterogeneity, Bernard et al. (2014) augment a trade model with buyer-seller matching costs and Carballo et al. (2013) focus on heterogeneity and selection into markets. Looking at the apparel sector in Bangladesh, Kamal and Sundaram (2013) find a significant effect of geographical proximity of suppliers in the likelihood of forming a link with a buyer, understanding proximity as a channel for information flows between sellers or to the buyer. Outside the trade literature also exploiting matched buyer - seller data, Andrabi et al. (2006), propose a model of pricing and asset specificity in relations between a tractor assembler and its suppliers in Pakistan and Vignes and Etienne (2011) look at the effects of connectedness on prices in the fish market in Marseille.

This chapter offers an exploration on the relation between heterogeneity across players and market outcomes in the context of relations between Ready Made Garment manufacturers in Bangladesh and their foreign buyers. The work presented here exploits a unique dataset that allows us to go one step further than previous empirical studies on interfirm relations: for the subsample of the data we are interested in, we can trace back the imported material inputs required for manufacturing the garments fulfilling specific export orders. For each shipment in our exports data, we can identify who the buyer and the seller are, link together shipments in the same order but spread in time and characterise the flows in terms of volumes and prices of output and inputs (mainly fabric). To the best of my knowledge, this is the first dataset containing information on input-output matches, at the level of disaggregation in our data and with its extensive coverage.

The contributions of this chapter are three. First, exploiting an econometric approach *imported* from the literature in Labour Economics, I offer a simple way of characterising exporters' heterogeneity moving away from the paths that related papers have chosen:

estimating firm-level productivity, eventually, via a structural model or assuming that the relevant dimension of heterogeneity is monotonically related to an observable characteristic that can proxy it, in general, exported volumes. The approach here recovers exporters' *types* under relatively mild assumptions with a simple procedure. Second, constructing a measure of heterogeneity, I document a novel fact on buyer - seller relations: in the presence of high heterogeneity across potential unknown sellers, a buyer allocates orders more frequently to his existing suppliers, relative to market conditions in which the heterogeneity of the alternatives is lower. While this is compatible with a number of existing theoretical models, the results presented here constitute, to my knowledge, the first empirical collection of evidence of this type. Third, exploiting a unique feature of our dataset, I find evidence of the existence of a 'premimum' for heterogeneity in the price - cost margins buyers afford. Again, without imposing the restrictions of a specific bargaining protocol, I show evidence indicating that markups in garment orders go up when the heterogeneity the buyer is facing in its outside option is high.

Section 2.2 presents the data briefly and describes the units of analysis. Then, a general, highly simplified model is presented to derive the main hypothesis. Section 2.4 is devoted to constructing the measures of sellers' heterogeneity. The subsections in 2.5 present the main analysis, exploring the two main market outcomes of interest: who trades with whom and what are the markups paid in the transactions. I close this chapter discussing the starting points for the modelling strategy in Chapter 3.

2.2 The Data

The empirical analysis in this chapter exploits a comprehensive dataset recording all export transactions between Ready Made Garment manufacturers in Bangladesh and buyers in the rest of the world. The original source of this dataset is the compilation of mandatory export and import records in the main Custom Stations in Bangladesh, between 2005 and 2012. Each record constitutes a product (Harmonised Codes disaggregated to the sixth digit) within a shipment from a supplier to a buyer, taking place on a given date. These are *real-time* records and include details on the statistical values, quantities, destinations and specifics of the terms of trade. Importantly, they include identifiers for all buyers and sellers. Full details on the construction of the dataset, its coverage, robustness checks against other official sources of data and cleaning and control of the players identifications are presented in Appendix A and Appendix B.

Although we observe trade in all the product categories within Ready Made Garment, we focus on this chapter in woven garments, unless otherwise stated for the purpose of specific references to knitwear. The exports of garment in Bangladesh are split almost half-and-half between knitted and woven products, in which I focus here. Details on this are presented in Appendix D. The main advantages of concentrating the analysis on this subcategory are: (i) that manufacturing technologies are known to be relatively homogeneous, across products and across firms, within the set of woven products; (ii) that the demand for garment from *large* buyers is concentrated in woven products (tables **??** and **??**);(iii) that most of the fabric required for producing woven garment is imported, a condition that we will exploit to produce input-output matches.

As well as the exports, our source of primary data includes all the imports by RMG manufacturers into Bangladesh, with records as detailed as those in the exports side of the data. Exploiting an administrative procedure necessary for claiming for duty exceptions when importing inputs for fulfilling garment export orders, we can match specific orders to the material inputs used for producing them (see Appendix D for a comprehensive explanation on this). Moreover, the RMG sector in Bangladesh being almost exclusively export oriented, means exported volumes coincide with virtually the whole of the manufacturers' supply. Therefore, we can claim we observe the firms' output entirely and, for the sample I will be working with, the relevant material inputs as well.

In the main woven categories, we observe approximately 5,000 buyers operating in the panel. Of all these, we can identify a small pool of *large* players that purchase woven garment in Bangladesh with Europe and the United States as the main destinations: every year, 0.2% of the buyers account for 40 to 50 percent of the demand for woven products and, while the demand from other *non-large* buyers seems to have reached a plateau, the demand coming from *large* buyers has expanded rapidly in the last years, pulling from the overall growth of the sector. The trade patterns of these large buyers are significantly different from that of the smaller counterparts. I will omit here a full description of these firm-level statistics, which the reader can find in tables C.14 to C.42 in Appendix C, to direct the attention to buyer-seller metrics.

Relations here, in its broadest definition, refer to pairs of buyers and sellers that are observed trading at least once in the panel [2]. Appropriate refinements will be introduced later. While buyer-seller pairs are the main focus of this chapter, some of the analysis is performed at a finer level of disaggregation.

We can group the transactions between buyers and sellers in two types: buyers can place *orders* to manufacturers or they can trade via *isolated shipments*. We can distinguish these two modes of trade, using information on the Export Procedures in our dataset (see Appendix B and Appendix D for details). The difference between the two modes is not

[2]The reader is again referred to Appendix B for various robustness checks performed on the identities of the players, among others, controlling for changes in identities over time.

merely administrative. *Orders* span over time, can entail multiple shipments, can involve multiple products, imply an ex-ante specification of quantities, input requirements and quality of materials and, notably, allow for import duty exemptions if fabric is imported for the purpose of fulfilling the order [3]. *One-off shipments*, on the other hand, do not entitle manufacturers to claim for import tax reimbursements and, obviously, stand alone as isolated shipments.

Large buyers mostly operate using orders, with almost 99% of the value of their exports in our panel falling under this system (see C.13 in C). For robustness, an exploration of the one-off shipments was carried out to conclude that there was no significant specialization pattern of sellers over the two modes of trade. Of all the sellers that trade at least once with large buyers in our sub-sample, only 25% of them have less than 99% of their trade channeled via orders. There are only a handful of manufacturers with large proportions of one-off shipments (up to 80% over their overall traded value) and these are mainly manufacturers that are not specialised in woven products and that feature negligible participation in our panel in terms of exported volumes [4].

Given this evidence, when we turn to more disaggregated descriptive regressions, we focus only on the trade between buyers and sellers that is done through orders, disregarding the isolated shipments, except otherwise stated. The dataset that we are exploring, then, contains information on every product in every shipment of all orders placed by buyers over the period January/2005 to September/2010 in any of the four major woven categories. This adds to a total of $100,382$ orders. Less than 20% of these belong to a dozen of *large* buyers and account for 40% of the traded values in our panel. Appendix J contains a brief fact-sheet for each of these *large* buyers, describing them qualitatively.

2.3 A Simplified Framework

Consider a highly simplified setting in which heterogeneous buyers and sellers meet to trade a given product.

[3]See Appendix D for the conditions for duty exemptions on imports for inputs for garment manufacturing.

[4]To rule out the possibility of overlooking strategic allocation decisions from the buyers over modes of trade, we corroborated that the probability of a shipment being channeled as a stand-alone transaction (as opposite to it being part of an order) is not significantly related to: i. the size of the shipment; ii. the woven product category; iii. whether the quarter in which the shipment is received corresponds to the first quarter of the buyer operating in the corresponding product category; iv. the *age*, measured in quarters of activity, of the buyer in the market; v. whether the demand from the buyer in the quarter-product is above its median demand; vi. observable characteristics of the manufacturer (a proxi for capacity and a proxi for quality, using import prices); vii. different forms of time effects.

Buyers and Sellers. There are $J \in \mathbb{N}$ manufacturers indexed by j, each of a different type θ_j, drawn from G^S, an Extreme Value distribution over $[0, \infty]$, with scale parameter $\sigma > 0$ and shape parameter α.[5] This is private information to each seller. There are also $I \in \mathbb{N}$ buyers indexed by i, that are either large or non-large, collected in disjoint sets with $I^L \bigcup I^{NL} = I$. Buyers willing to trade draw costlessly and randomly a seller from the set of all available manufacturers. For simplicity, all sellers are drawn out with equal probability. Upon matching, the buyer privately learns the type of its potential supplier.

Production of value. When buyer i and manufacturer j trade, the net unit value generated in the relation is $v_j = \theta_j F(X_{ij})$. X_{ij} collects buyer-seller specific variables, in particular, the inputs used in the production of the item. Note that the technology is the same for all buyers and sellers, up to a multiplicative idiosyncratic seller effect. Sellers of low type only deliver successfully a small fraction of value they produce, while sellers of high type shift the per unit value up.

Surplus division. If trade is not consummated between buyer i and seller j, the manufacturer pays no cost and renders no profit from the relation. This is the case also for non-large buyers. Large buyers, on the contrary, can take control of all X_{ij} material inputs and attempt production with an alternative supplier k, whose θ_k is ex-ante unknown. When trade is consummated between buyer i and a manufacturer, the value generated in the match is split between the seller and the buyer, with shares β_i and $(1 - \beta_i)$, respectively, for $\beta_i \in (0, 1)$. The bargaining parameter is buyer specific and exogenous.

Prices. The unit surplus from the transaction between large buyer i and seller j, relative to an alternative k, can then be written as $s_{ij} = (\theta_j - E[\theta_k])F(X_{ij})$. With the sharing rule described above, prices are $p_{ij} = \beta_i F(X_{ij})[\theta_j - (\sigma(\Gamma(1 - \alpha) - 1)/\alpha)]$, where the second term in the square brackets comes from the shape of G^S and $\Gamma(.)$ denotes the gamma function. For ease of exposition, we can define $\tilde{\theta}_j = \theta_j/\sigma$ to be the scale-adjusted type of seller j. Prices can then be rewritten as:

$$p_{ij} = \beta_i \sigma F(X_{ij})[\tilde{\theta}_j - (\frac{\Gamma(1 - \alpha) - 1}{\alpha})] \tag{2.1}$$

Note from here that there are gains from trade and prices are positive whenever $\tilde{\theta}_j > ((\Gamma(1 - \alpha) - 1)/\alpha)$, which is the condition for trade with large buyers, in the absence of

[5] The location parameter is adjusted for a distribution with positive support.

switching costs. Note also that increases in the spread of the distribution of types, α, bring prices up. [6]

The basic setup above induces a number of hypothesis that can potentially be tested in the data. First, other things equal, higher types of suppliers obtain higher prices. Second, higher heterogeneity in the types of suppliers in the market, results in higher prices. Third, conditional on the type of the incumbent supplier, the higher the heterogeneity in the market, the more likely the buyer is to stay with its supplier. Fourth, low type suppliers only trade with 'non-large' buyers.

2.4 Measuring Heterogeneity

Testing the hypotheses described above requires the econometrician to know (or estimate) players' types, unobservable in our setting.

The recent studies exploiting matched exporter – importer data have conceptualised firm heterogeneity either focussing on productivity and efficiency or on quality. As rich as newly available custom datasets are, direct measures of either of these have proved difficult to construct. Most papers have used traded volumes (size) as a proxy for the unobserved dimension differentiating manufacturers. Others have used volumes or values to recover parameters of the distribution of such unobservables, as a factor in a parametrised technology. An alternative to this has been to use unit prices, when available, as a proxy for a latent variable in which prices or values are assumed or shown to be increasing.

Our data allows us to go one step further than previous studies. We will exploit the fact that we observe both volumes and prices at a disaggregated level to obtain (scalar) measures of heterogeneity of manufacturers, using relatively light assumptions.

The operational definition for heterogeneity will be that sellers that, conditional on the product, at a given price can sell higher volumes are recognised by the demand as better suppliers. Prices of inputs are used as a proxy for the overall product (and seller) quality. This is an innocuous assumption in the context of garment production, where high quality pieces are produced with better fabric, which in turn constitutes not only the bulk of the weight of the garment but also the largest component in the per-unit cost.

[6] Recall α is the shape parameter. Therefore, for fixed scale, for example at $\sigma = 1$, increases in α move the distribution from being right skewed (towards zero) and high peaked to being left skewed.

For an order of certain quality and price, placed by a buyer i, in a given product category m at a point in time, the manufacturer's average deviation of the expected quantity reveals its type.

$$q^g_{ojimt} = \alpha^g + \alpha^g_t + \alpha^g_m + \rho^g_i + \theta^g_j + \delta^g p^f_{ojimt} + \gamma^g p^g_{ojimt} + X'_{ojimt}\beta^g + \eta_{ojimt} \tag{2.2}$$

From the equation above, the θ^g_j intercepts are extracted as a measure for sellers' types. The α^g_t terms collect fixed effects for the time period in which the order is placed (in quarters), the product category and an overall intercept. ρ^g_i constitutes a buyer fixed effect, such that the θ^g_j are shifters with respect to the average sized order by the corresponding buyer. The price of the fabric, p^f_{ojimt}, is included as a control for the quality of the product and the price of the output, p^g_{ojimt}, is also conditioned upon. Other controls include the material of the fabric used (cotton, synthetics, etc.), other – non-fabric – imported inputs, the mode of transport, the Customs Port and the terms of trade.

In terms of the econometrics involved in this exercise, the procedure mimics the type of estimation that has been used in the Labour literature in the tradition started by Abowd et al. (1999) (and subsequent papers of the same authors), exploiting employee-employer matched data to recover firm and individual fixed effects from wage equations as a measure of unobserved productivity, ability or the *types* of the players (some applications are those in Becker (2005)) on returns to seniority, Woodcock (2003) on heterogeneity and worker-firm learning and Barth and Dale-Olsen (2003) on annotativeness). The underlying assumption in all these applications is that after including the appropriate controls, fixed effects recover the relevant dimension of the unobserved heterogeneity.[7]

Like in the relevant literature, the successful recovery of players types in the context of our assumptions depends on the number of 'movers' each player is connected to. This implies that not all fixed effects are identifiable. In particular, those buyers and sellers that have few interactions within the panel and, even more so, restricted to one trade partner only have no fixed effect estimated, which tends to select against small players.

[7]Estimating these many fixed effects with standard techniques introduces the typical problems in the computation of a generalized inverse of the estimation matrix in the normal equation, involving very sparse matrices. I follow the approach presented in Abowd et al. (2002), who develop a method to solve exactly the least squares problem in this setting, grouping the data in the "components" of the network, which is proved necessary and sufficient for the estimation of both fixed effects for most of the buyer-seller pairs. The procedure consists of dividing the data in the fully connected subgraphs that are not inter-connected with each other (the "components"), sweeping out one of the fixed effects using a within transformation and calculating the fixed effect of the other set of players by introducing individual dummy variables. Those components in which a buyer has only sellers that don't trade with other buyers, the buyer fixed effect cannot be estimated. Full details on the estimation procedure can be found in Appendix I.

The specification above recovers fixed effects for sellers that account jointly for 83% of the trade in woven garments in the panel.

A parametrisation of the distribution of types of suppliers present in every product category was obtained by fitting, via maximum likelihood, three parameters of a Generalised Extreme Value distribution. A first observation of the resulting distributions shows two features.

First, aggregating HS6 codes by broad product categories that identify the gender and general class of garment, we can see that products that are typically more fashion sensitive exhibit higher dispersion of seller types.

Table 2.1: Variance of Types of Suppliers per Broad Product Category

Borad Product Category	Variance
Female Dresses	2.3681
Female Trousers	1.7288
Male Suits	1.4781
Female Jacket	1.4219
Female Skirts	1.4104
Female Ensamble	1.2129
Male Jacket	1.1539
Male Ensamble	1.0670
Female Shirts	1.0438
Male Trousers	0.9362
Male Shirts	0.8746

The 48 HS codes disaggregated to the 6^{th} digit were grouped in 11 broad categories. Note that women's ensambles are pooled together with women's suits. The variance is computed using the shape and scale parameters in the fitted generalised Extreme Value distributions and are highly correlated (0.92) with the empirical variances computed directly from the data, when data is de-meaned to be centred around zero.

Fashion sensitive products are usually supplied through shorter orders, with quicker lead times and where a higher proportion of the order is delivered in the first shipment. Looking at the median duration of the orders in each product category as a proxy for fashion sensitivity, we can see that the raw correlation of this proxy and the standard deviation in seller types lies between -0.69 and -0.76 (depending on how the duration variable is constructed). This means that the shorter the duration of the median order (or, the more fashion sensitive the product), the higher the dispersion in types.

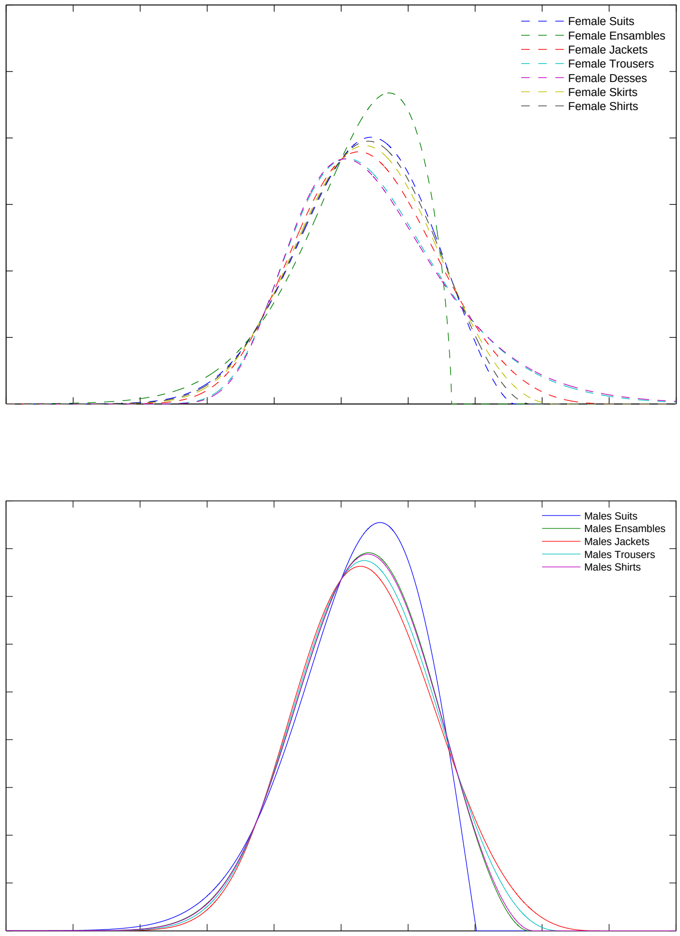


Figure 2.1: Probability Density Functions Based on Estimated Parameters per Broad Product Category.

Graphs show generated probability density functions based on the parameters (location, scale and shape) fitted via maximum likelihood. The right panel correspond to female product categories and the left panel, to male categories. The location was adjusted for each curve so all overlapped curves would share the same mean. All graphs are generated in Matlab.

Second, grouping the buyers in large and non-large, we can see that the distribution of types of suppliers that trades with one and another group are of similar shape, with a shift to the right in the case of manufacturers that supply to large buyers.

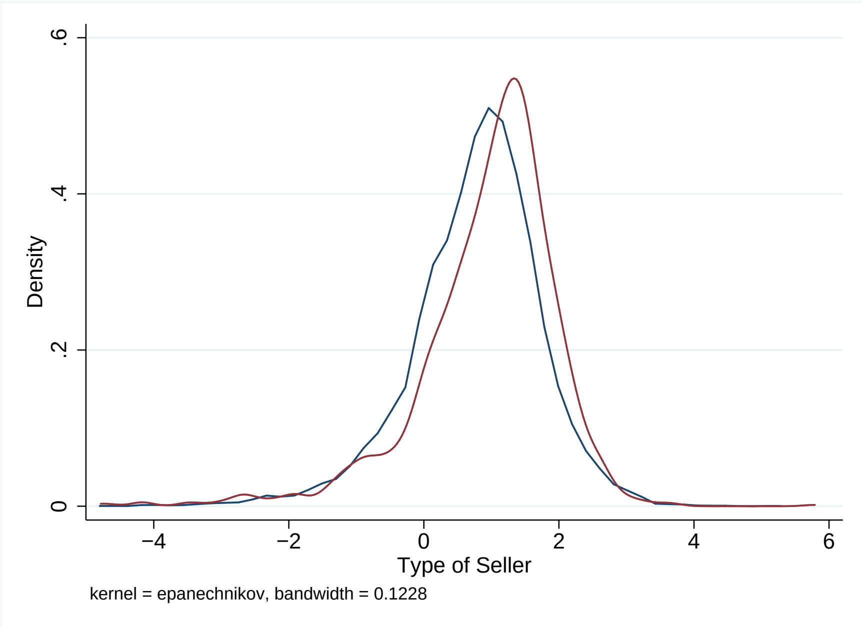


FIGURE 2.2: Kernel Approximation of Distribution of Types of Suppliers - Large and Non Large Buyers.
Kernel approximations are generated in STATA, using Epanechnikov. The types are de-meaned to center around zero. The blue line corresponds to non-large buyers and the red line corresponds to large buyers.

2.5 Heterogeneity and Market Outcomes

2.5.1 Persistency in Buyer - Seller Relations

The first market outcome to investigate is the *network* of relations that support trade in each market. At every point in time, we observe specific pairs of buyers and sellers trading. This market outcome can be conceptualised as the result of multiple buyer-level decisions of allocating every order it demands to a supplier, out of a choice set of available manufacturers.

I simplify this decision into a binary choice, made by the buyer, of allocating the order to an existing supplier or to a new supplier. A strictly positive outcome in this binary choice signals persistency in the choice of suppliers, favouring already known manufacturers. The main interest lies on the effect, on this outcome, of the heterogeneity the buyer is facing across its potential suppliers.

This requires specifying two operational definitions. The first one is that of an *existing supplier* from the perspective of a buyer and I will assume that an existing supplier is a manufacturer the buyer has traded with in the last year in any product category. The second one involves defining the set of *available suppliers* to the buyer, this is, the set of manufacturers the buyer considers as its potential supply when facing the decision to allocate an order.

As in many discrete choice problems, our data collects consummated trade, this is, ex-post decisions. In this context, the set of suppliers available to the buyer constitutes a hypothetical choice set for the relevant decision. Actual choice sets are unobserved and presumably exhibit large variations across decision makers. The baseline definition will be that all buyers face the same set of available suppliers in a product-quarter combination, and therefore, are exposed to the same 'amount' of heterogeneity.

Numerous alternative definitions can be presented and, in particular, I will use the information we have on the actual allocation to weight the types of the suppliers when constructing the variance as a proxy for the heterogeneity the buyer is facing. Of all the suppliers that in the year of allocation of the order are active in the corresponding product category, I give higher weight to the subset of manufacturers that are 'closer' to the manufacturer that is selected ex-post by minimizing a score based on three observable characteristics. For each pair of observations, formed by the actual supplier of the order and another manufacturer available in the market, the measure is constructed as the weighted product of distances between observations in the three variables, where weights are given by the corresponding covariance matrix [8]. The selected variables collect the quality of the input used by the seller -measured as the average price of the fabric used by the manufacturer up to the corresponding date-, the experience of the supplier -measured in the number of quarters it has been producing the item-, and an approximation of the *segment* of the market in which the seller operates -measured as the median buyer he is used to serve, ranked by its location in the normalised distribution of prices. This alternative is presented in the Appendix.

The baseline specification of interest describes the probability of an order o for product m being allocated at time t by buyer i to any existing supplier. Note that in our panel, an order identifies m, i and t uniquely, so part of the subindexing below is redundant, but hopefully clarifying.

$$Pr(a^K_{oimt} = 1|X, \hat{\theta}) = \Phi(\alpha + \beta_0 \bar{\hat{\theta}}^k_{oimt} + \beta_1 \bar{\hat{\theta}}^u_{oimt} + \beta_2 StDev(\hat{\theta}^u_{oimt}) + X'_{oimt}\beta) \qquad (2.3)$$

The outcome variable a^K_{oimt} takes value one if order o, in product category m at time t, is allocated to a supplier that is known by buyer i. Recall θ_j constituted the the seller fixed effect obtained in the previous section, as a proxy for the type of the supplier. $\bar{\hat{\theta}}^k_{oimt}$ is the average type of the known or existing suppliers to buyer i, relevant to the current order. Similarly, $\bar{\hat{\theta}}^u_{oimt}$ denotes the average type of all available suppliers that are

[8]For pair (i, j), for instance, $\Delta'_{ij} W \Delta_{ij}$, where Δ_{ij} is a vector whose k^{th} entry is defined as $x^k_i - x^k_j$ and W is the covariance matrix over all k's. Note this is the square of Mahalanobis score.

unknown to the buyer. $StDev(\hat{\theta}^u_{oimt})$ is the standard deviation across these unknown suppliers. X_{oimt} contains other covariates, including buyer, product and quarter fixed effects, counts of known and unknown players on each side of the market, the size of the order and the size of the overall demand in the product - quarter combination. The table below presents the results from a Maximum Likelihood Probit estimation following the equation above.

Table 2.2: Probability of allocating an order to a known seller - Probit Marginal Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Av. θ known suppliers	0.050***	0.007***	0.032***	0.007***	0.007***	0.008***	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Med. θ unknown suppliers	0.008		0.016	0.014	0.003	0.008	0.026
	(0.02)		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
St.Dev. θ unknown suppliers	0.041**	0.032**	0.037**	0.030*	0.032**	0.034**	0.023
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Av. θ unknown suppliers		0.013					
		(0.02)					
Volume order, logs				0.033***	0.033***	0.033***	0.022***
				(0.00)	(0.00)	(0.00)	(0.00)
Volume demand (prod-quart), logs				0.003	0.025***	0.014**	-0.004
				(0.00)	(0.01)	(0.01)	(0.00)
Number of buyers, logs					-0.055***		
					(0.01)		
Number of available suppliers, logs						-0.029**	
						(0.01)	
Ratio known to all suppliers, logs							0.064***
							(0.00)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes	Yes	Yes
Observations	79892	78809	79892	78809	78809	78809	78211

An observation in these estimations is an order. The outcome takes value one if the order is placed with an existing supplier of the buyer, according to the definitions in the main text. Standard errors are bootstrapped in all cases, clustering the re-sampling by broad product categories. Products are organised in HS6 categories.

Across all specifications above, we corroborate that the probability of re-allocating an order to the pool of known manufacturers is increasing in the average type in the pool. However, this effect is not dramatically large. A unit increase of the corresponding covariate would imply shifting that average, from the median to the 95^{th} percentile, jump that would induce an increase in the probability of allocating orders to the known suppliers of around 1%. While the median (and average) type of the unknown suppliers does not have a significant effect on the outcome, increases in the deviation of types of the unknown suppliers increase (3 to 4%) the probability of allocating orders to existing suppliers. Note that the only specification in which the standard deviation of unknown types does not affect significantly the outcome is that that accounts for the proportion of known suppliers over all available suppliers, in Column (7). Other things equal, an increase in this ratio would reduce the number of unknown suppliers, which in turn decreases the denominator of the standard deviation of unknown types. An effect of magnitude similar to that of the heterogeneity across available suppliers is induced by larger orders. In terms of volumes, orders 1% larger have a higher probability (0.03) of being sourced from known manufacturers.

2.5.2 Profitability and Price-Cost Margins

I now turn to exploring the evolution over time of price-cost margins in the orders placed by a buyer to its supplier. The regressions below have as cross-sectional units all the orders between large buyers and suppliers. As explained above, orders span over time and for the purpose of these regressions we consider them to be dated by the date (aggregated in quarters) of the first shipment in the order. Orders in a trading pair are then arranged by date and numbered subsequently. This numbering constitutes what I call the *Linear Trend* in the regressions below, and a unit increase is an additional order placed by the buyer to its supplier. I exclude below all the relations that last for less than a year, as the focus here is on the evolution of surviving relations.

The outcome variable is the price-cost margin in each of these orders and is denoted μ_{ijoks}, varying at the level of the order o, placed by a buyer i to a seller j, in product m in sequencing time s. Note that m is specific to o and the triplet ijs fully defines o so notation here, is again technically redundant.

$$\mu_{ijoms} = \alpha + \alpha_{ij} + \delta_m + \iota_{t(o)} + \gamma_1 s + X_{ijoms}\beta + \epsilon_{ijoms} \tag{2.4}$$

Note that $\iota_{t(o)}$ introduces seasonal corrections based on calendar times t of order o. Dummies for the buyer-seller pair, products and seasons are kept in all regressions. The outcome variable is defined by the difference between revenues and costs, as a proportion of the costs (i.e., (PQ-C)/C).

Across all specifications, we observe a small positive effect of every additional order in the relation. Across all pairs in the data, the average number of orders in the relationship is 3.6, although a large share of the trade takes place in the top tail of the distribution of number of orders in the relation, which, on the 95^{th} percentile is 12. The average price of the fabric used for producing the garment and the size of the order are both negatively related to the margin over costs. The number of buyers allocating orders in the relevant product - quarter combination seems shows a positive effect in the price - cost margins. An expansion of the demand of 1% - again, measured via the count of buyers - is associated with margins 0.085 higher.

Of substantive effect is the role of the type of the supplier, proxied by the fixed effects in the volumes equation. A shift of a supplier from a score that would place it at the median of the distribution of types to the 90% percentile induces increases in the price - cost margins of 0.23, other things equal. Conditional on the type of the supplier, we also observe, despite the large standard errors, a strong positive effect in markups with increases in the dispersion of types the buyer is facing. Now, the standard deviation is measured over all alternative the buyers could have allocated the order to. This then, represents the heterogeneity across the buyer's outside option to the incumbent relation.

Table 2.3: Price Cost Margins

	(1) markup_all	(2) markup_all	(3) markup_all	(4) markup_all	(5) markup_all	(6) markup_all
Linear Trend	0.001**	0.001*	0.001**	0.001*	0.001*	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Av. Price Fabric, logs	-1.085***	-1.086***	-1.085***	-1.095***	-1.096***	-1.097***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Volume order, logs	-0.131***	-0.131***	-0.131***	-0.147***	-0.148***	-0.148***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number buyers, logs		0.084*				0.087*
		(0.05)				(0.05)
Volume demand (prod-quart), logs			0.039			
			(0.03)			
θ supplier				0.238***	0.235***	0.235***
				(0.03)	(0.03)	(0.03)
Av. θ alternative suppliers					0.083	0.100
					(0.08)	(0.09)
St.Dev. θ alternative suppliers					0.110*	0.102*
					(0.06)	(0.06)
Constant	4.722***	4.348***	4.201***	4.656***	4.506***	4.113***
	(0.15)	(0.29)	(0.43)	(0.17)	(0.22)	(0.38)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Buyer-Seller FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53848	53848	53848	53848	53762	53762
R^2	0.611	0.611	0.611	0.612	0.613	0.613

An observation in these estimations is an order. The outcome variable is measured as (revenue - cost)/cost, which in the data, across all product categories and time periods, has a median of 0.87 and a Standard Deviation of 1.3. Standard errors are bootstrapped in all cases and clustered by HS6 categories. Time fixed effects are taken according to the quarter in which the order starts, irrespective of its span over time. Product fixed effects correspond to HS6 codes.

2.6 Discussion towards a Model of Network Formation

The analysis above presented a selection of reduced-form explorations that aimed at understanding aspects of the evolution of relations between buyers and RMG manufacturers in Bangladesh. In Chapter 3 I present a dynamic game of network formation that accommodates this evidence. The formulation I present has four key ingredients. Every period, each buyer decides which seller, out of the available suppliers, to allocate her order to, paying a *sunk cost of linking* whenever choosing a new supplier. These uncoordinated decisions set a *bargaining network*, where the linked pairs Nash bargain over prices. The inside and outside values of a relation include both the *current and future flow of profits* and take into account the effects of linking choices on future transitions over states. Importantly, the outside options of the parties are determined by the links in the negotiation network. Finally, I allow for *matching-specific qualities* that are payoff relevant for the buyer.

Persistency in the model I propose is induced both by the cost of linking and by the presence of heterogeneity at the matching level. In a somehow similar setting, Monarch (2013) finds evidence supporting strong recurrence in relations between international buyers and suppliers in China, even when a large number of alternative suppliers are available. To conceptualise this, he proposes a (single-agent) dynamic discrete choice model in which buyers choose a supplier, evaluating the trade off between the gains from switching to manufacturers with lower prices (or higher quality) and the cost from switching. At the agent level, the formulation I propose coincides with the discrete choice structure, in that the buyer evaluates in a dynamic framework the potential gains of trade with the suppliers available to fulfil her order.

Bernard et al. (2014) propose a trade model with heterogeneous parties, featuring a fixed cost of forming a relationship. In their formulation, the seller bears the whole of this fixed cost, which is conceptually associated to tailoring the output to the buyer's need or to bureaucratic procedures starting a new export contract. In a search-and-matching setting, Eaton et al. (2014) model the decision to either continue the relation with the current trade partner or to search for a new partner on the seller's side entirely. Unlike these two approaches, the model I propose is compatible with an interpretation of the cost of linking as a sunk cost the buyer needs to incur. This follows the anecdotal evidence gathered in conversations with large buyers, who describe a costly process of screening, visiting production plants, testing, adjusting designs and running quality checks, before they can place an order to a new supplier.

Unlike the empirical observations in Monarch (2013), in our setting higher prices are associated with relations that are *more* likely to survive. This, together with evidence showing that sellers capture higher profit margins when competing large buyers are present in the market, implies a *switch-or-stay* rule slightly different to the one in Monarch (2013). The game I propose captures this new evidence via its networked structure: as sellers are capacity-constrained, having an additional large buyer willing to trade with her increases (potentially) the outside option of the seller when bargaining with its current partner. If the value of the relation with the seller is high enough the price is higher than in the state without a competing buyer and the link remains active.

The formulation I present in the following chapter accommodates a dynamic aspect to the bargaining stage, after the cost of linking is sunk. The optimal price in a relation and, consequently, the current and future value of that link, depends on the transition probabilities over states, which are an indirect function of the costs of breaking and forming new links. This aspect of the proposed model, resembles Kleshchelski and

Vincent (2009), who, in a macro framework, find that when switching costs are low, buyers are more likely to break the current relationship, and therefore the (future) value of that buyer to the supplier decreases. In their setting, this has an impact on the price the seller sets for its product, where a larger fraction of marginal costs is passed-through to the buyer via prices. In the opposite case, when the cost of dropping the current seller and buying from an alternative one increase, the value of the buyer increases and pass-through goes down.

Chapter 3 is then devoted to the formal presentation of a dynamic game of network formation, with endogenous bargaining. I also present a computer realisation of the game, using simulations to show the relation of the key parameters of the model with the evidence presented in this chapter.

Chapter 3

A Dynamic Game of Linking and Bargaining

3.1 Introduction

The production of Ready Made Garment in Bangladesh is mainly export-oriented. Manufacturers supply knitted and woven garments to buyers from all over the world, with Europe and United Stated as the main destinations for their exports. *Large* buyers account for the best part of the expansion of the exports in the sector in the last decade. Then, uncovering the mechanisms driving their choice of suppliers and the determination of prices are key for understanding the evolution of the industry and, with it, the development path of the country.

The results presented in the previous chapter show at least three relevant features of the relationships these buyers establish with garment suppliers in Bangladesh. First, relationships exhibit persistence and buyers tend to re-trade with their existing suppliers over time. Second, the unit price the buyer pays for the garment is affected by the presence of other large buyers in the market, potentially willing to allocate orders to the same suppliers. Third, heterogeneity at the seller level plays a significant role in the linking decisions.

This chapter proposes a model that realises those patterns in the data, governed by the interactions between players' heterogeneity and buyers' competition for suppliers. Using data on buyer - seller matches and prices, I am able to estimate structurally the parameters underpinning large buyers linking behaviour. To do this, I use a model of dynamic network formation with bargaining, first proposed in Lee and Fong (2013). The game I present describes the dynamics inducing two observable outcomes in this market: the trading partnerships (or who links with whom) and the contracts or prices between the linked parties. In Chapter 4, using records from every transaction I observe between manufacturers in Bangladesh and large buyers in the rest of the world, over a real-time panel, I discuss alternative procedures to recover the relevant underlying parameters. The modelling strategy here serves then two purposes. The first one is to offer a semi-formal framework that can help understand the evidence we collect from the markets we are interested in, in terms of the forces driving the industry dynamics and its institutional environment. The second one is to build a structure that can aid the recovery of the underlying parameters that govern those dynamics, using techniques that circumvent the problems that arise when estimating high-dimensional dynamic problems like the one at hand. While this chapter will introduce references to literature on the estimation of dynamic oligopoly games, the main discussions concerning this literature and the econometric approach are left for the following chapter.

The players in the game are either *buyers* or *sellers* of RMG. In each time period, players have two decisions to make: (i) buyers need to choose a supplier for their orders and sellers need to accept supplying the garment if invited to do so and (ii) for the partners that agree on trading, a bargaining process will determine the price for the garment. The formulation presented here will show four key features. It represents a *dynamic* game, featuring a sunk cost - to the buyer - of forming a relationship. It is *networked*, in the sense that prices, and ultimately the probability of observing a given trade partnership, depend on the linking choices of other players. It allows for *matching heterogeneity*, as a cost-reducing component in the profit function for buyers and it accommodates *non-symmetric bargaining* in the pricing problem.

The main idea that drives this chapter is that **the observed trade network and prices are the result of a dynamic process in which buyers, heterogeneous in the surplus they can extract from the seller, compete for suppliers, heterogeneous in the value they can produce in partnership with each buyer**.

In its general structure, the game presented here is that of a multiple-agent dynamic game with incomplete information. This paper, then, is closely related to the literature in Industrial Organisation that builds on Ericson and Pakes's framework to study industry dynamics, adding incomplete information to their general setting (1995). A number of applied papers have exploited this set up to describe various institutional environments. Applications have been focussed on different versions of entry / exit problems, with choices on capacity, quantities, integration or mergers, of which some interesting but in no way exclusive examples can be found in Ryan (2012), Aguirregabiria and Ho (2012), and Gowrisankaran (1999). Within this tradition, the applications that are more closely related to the one at hand are those that, like in our setting, propose quantity or pricing sub-games whose resolution affects future periods' choices, therefore affecting the conditional probability of future states being observed. This involves *nesting* the computation of the stage profits inside of the dynamic programming problem defined by the corresponding value functions. Examples of games with these features can be found in Benkard (2004) on learning-and-forgetting and Markovich and Moenius (2008) on hardware platforms and software choices, among others.

To the best of my knowledge, there are only a few studies that analyse industry dynamics in the light of *networked* strategic interactions. Notably, the work by Aguirregabiria and Ho on the US airline industry, study the relations between hub-spoke networks with entry costs and entry deterrence effects (2010; 2012). An 'aggregation' assumption suitable to their setting circumvents some of the complications the networked structure imposes in the formulation I present here.

The "outer" layer of the game is a dynamic discrete choice linking problem, in which buyers simultaneously choose a supplier from a list of available heterogeneous manufacturers, in order to maximise inter-temporally the profits made in trade. In the "inner" layer, linked pairs bargain over prices with outside options in a Nash bargaining setting determined by the network of links. The specifics of the bargaining stage in the game I propose resemble the exercise in Dranove et al. (2011), whose theoretical construction follows Stole and Zweibel (1996). The distinctive feature of my game is that the evaluation of disagreement points accounts for the effects of disagreement in current negotiations and the future realisations of the network. In my setting of simultaneous bargaining, a seller negotiating prices with two buyers will consider as disagreement payoffs for each of these buyers no longer the price she would obtain from a second buyer under the current setting, but the one she would obtain if the link with the first buyer was dissolved after disagreement. This lowers the outside options relative to a simpler and potentially more naive view of renegotiations[1][2] .

In terms of the computation of the game I propose, as in Lee and Fong (2013), I exploit a number of well established results in structural industrial organisation and numerical methods. These help deal with dynamic programming problems, its specificities when applied to multi-agent environments and to incomplete information settings, the associated computation algorithms and the issues around existence and multiplicity. The developments that are most relevant to what is presented here are those in Aguirregabiria and Mira (2002); Doraszelski and Pakes (2007); Doraszelski and Satterthwaite (2010); Hotz and Miller (1993); Pakes and McGuire (1994); Rust (1994).

[1]Lee and Fong's setting accommodates this alternative.
[2]Subject to parameters, but in the majority of the cases.

The following section presents an intuitive description of the game and describes its timing, while Section 3.3 deals with the presentation of its formal aspects, and addresses briefly issues around existence and uniqueness. These are further discussed in relation to computational matters in Section 3.4, which offers evidence on a computer exercise that finds equilibria of a simple version of the proposed game over a grid of candidate parameters. In Section 3.5 the key interactions between the parameters of the game and the observable market outcomes are presented.

3.2 Intuition and timing

The model described below constitutes an application of the general framework developed in Lee and Fong (2013). Lee and Fong's structure follows Myerson's network formation game in that players announce links so that the bilateral intersection of the choices of players gives a negotiation network (Myerson, 1991) [3]. In the game below, I will consider that buyers announce the links they want to form and sellers make no choice around who they negotiate with at this stage, so the negotiation network is fully determined by the decisions on the buyers' side. Moreover, I focus on the *main order* the buyer needs to place and I consider buyers' action space is such that they can only choose one seller to negotiate with at a time. These restrictions, accommodate the empirical application at hand and make the outer problem of the game resemble those in standard entry / exit dynamic settings.

Once the negotiation network is set, all the linked pairs simultaneously engage in Nash bargaining to determine the equilibrium contracts. Prices are solved for, whenever possible, splitting the surplus of the relationship given the bargaining power at each end of the negotiation. Disagreement points in this stage incorporate two main features: first, they account for future changes in the network, allowing for the exploration of dynamic aspects of strategic linking and, second, they depend on other links the seller might have, generating competition between buyers. In this process, for some sets of parameters and continuation values, pairs linked in the negotiation network might fail to reach a viable agreement. The final trading network is then a subgraph of the negotiation network.

Attention here will be restricted to (pure strategies) Markov Perfect Equilibria (Maskin and Tirole, 1988), as it is most common in the associated literature. I am going to omit the discussions on the potentially (non) testable implications of this equilibrium concept and its relation with alternative concepts, such as oblivious equilibria (Weintraub et al.,

[3] There is a vast literature elaborating on strategic network formation processes alternative to Myerson's simultaneous link announcement protocol. See Jackson (2004) for a survey.

2008) or self-confirming equilibria (Fudenberg and Levine, 1993). The reader is referred to these papers and Maskin and Tirole (2001) and Maskin and Tirole (1988) for a more systematic presentation of the applicability of the Markov concept to games of the type we are interested in.

There are four exogenous primitives of this game. First, before the start of the game, each buyer solves a demand problem in their own end market to determine a (fixed) retail price for the garment. This remains unchanged throughout the game, it is buyer-specific and it is taken as exogenously given. At the same time, buyers decide the size and quality, determined by the price of the main material input (fabric), of a *single* order to be placed and these also remain constant throughout the game. Within a given product category, this can be viewed as the buyer's *main order* of the product in a time period [4]. Together with the choice of the size of the order, buyers decide the quality (price) of the fabric they will require. Second, at the beginning of the game, each buyer-seller pair is endowed with an *observable* quality for their match, fixed throughout the game and payoff relevant for the buyer[5]. The matching quality enters additively in the profit function of the buyer: trading with a worse supplier imposes an additional per-unit cost for the buyer. One way of interpreting this is that a lower match will force the buyer to incur in extra costs for quality control purposes, monitoring, failures in the product development stage or simply that a fraction of the value of the garment gets destroyed. Third, forming links is costly. There exists a publicly known sunk cost for starting a new (relative to the immediate previous network) relation and a cost for maintaining an old relation, both of which are fully afforded by the buyer. This sunk cost is a parameter of the model and it induces the dynamic aspect in the linking decision. Fourth, sellers are capacity constrained so each period they can only produce for one buyer.

Under those primitives, the game develops in two stages.

Network Formation: Buyers observe the network of relations that is standing and a shock to each possible action they can choose in the linking stage. Actions in this context involve the choice of (at most) one seller from the set of possible suppliers of garment. Upon (privately) observing choice-specific shocks, buyers simultaneously announce the seller they are willing to start negotiations with and pay the corresponding linking cost, if applicable.

[4] The single-order assumption can be easily relaxed in the empirical application. At this stage, focusing on one order per buyer simplifies the notation and will significantly reduce the state space, which will allow for an easier estimation of an equilibrium of the example game. In addition, for narrowly defined markets, it can be seen that large buyers allocate one main order and, eventually, a second small one, negligible in terms of size, relative to the first one.

[5] The observability of the match-specific quality will be discussed in more depth in Chapter 4. For the rest of this chapter, this is going to be treated as a know constant scalar for each buyer-seller pair.

Bargaining on Prices: Given those announcements, a negotiation network is formed and the pairs linked in the network bargain to reach a contract that maximises the Nash product of their inter-temporal gains from trade. These are determined by the structure of the standing network and the anticipated changes to the network in the future, upon a potential failure in contracting. Prices are solved for and a stable network is found, such that each seller has at most one buyer. Profits are realised and a new period starts.

The following section formalizes the game described above.

3.3 The Game

Let $\overline{B}$ constitute a set of buyers indexed with $i = \{1, \ldots, B\}$ and $\overline{S}$ a set of sellers individually denoted with $j = \{1, \ldots, S\}$. At any point in time, the -fully observed- bipartite network of links between buyers and sellers defines the state of the system. A link between players i and j under a given network g is labeled ij, denoted $g_{ij} = 1$ and represents potential trade between those players. Similarly, $g_{ij} = 0$ implies that buyer i and seller j are not trading under network g, so networks are formed as $g \subset \{0, 1\}^{B \times S}$. Let $\mathbf{G}$ be the set of all possible networks. I will use g_{-ij} to denote the network resulting from deleting the link between i and j from graph g. Finally, g_i designates the subgraph for player i. When ambiguity is possible, $g_{k\cdot}$ or $g_{\cdot k}$ will be used to distinguish buyers from sellers, with the first index corresponding always to buyers. Time evolves discretely over periods $\tau = 1, 2 \ldots \infty$.

3.3.1 Per-Period Profits

At a given point in time, per-period payoffs for each player ι, $\pi_\iota(.)$, are a function of the standing network and its associated negotiated transfers between linked pairs. $\pi_\iota(g, \mathbf{t}_g)$ is assumed to be continuous in $\mathbf{t}_g = \{t_{ij;g}\}_{ij \in g}$, containing the per-period prices agreed upon bargaining between all the agents that are trading under network g. $\mathbf{t}$ is defined in space $\mathbf{T} = \mathbb{R}$.

I will restrict attention to the networks in which each buyer can buy from at most one seller at a given point in time, $\sum_j g_{ij} \leq 1 \forall i \in \overline{B}$. At the same time, each seller will only be able to supply the good to one buyer, at most, so $\sum_i g_{ij} \leq 1 \forall j \in \overline{S}$.

Consider a buyer indexed with i and a seller indexed with j and assume they are linked under network g, so $g_{ij} = 1$ in period τ. Assuming away action shocks, which will be introduced later on, the per-period profit function for i is given by:

$$\pi_i^b(g^\tau, \mathbf{t}) = \sum_k^S g_{ik}^\tau \times [(r_i - t_{ik} + \rho_{ik})q_i] - c_i(g^\tau|g^{\tau-1}) = (r_i - t_{ij} + \rho_{ij})q_i - c_i(g^\tau|g^{\tau-1}) \quad (3.1)$$

Note that q_i, the quantities demanded by buyer i, are independent of j and so is r_i, the price the buyer charges in its end market for the garment. Both q_i and r_i are exogenously determined. In our context, t_{ij}, the equilibrium price for the garment in the buyer-seller transaction, is an intermediate price in the sense that it is the price the garment manufacturer charges the retailer, who in turn sells the garment to consumers at a price r_i. In addition, ρ_{ij} represents the match-specific component and it is exogenously given and known (for now). Finally, c_i represents the cost that buyer i pays for moving from network $g^{\tau-1}$ to network g^τ.

Similarly, the period profits for seller j in the network g are:

$$\pi_j^s(g^\tau, \mathbf{t}) = \sum_k^B g_{kj}^\tau \times (t_{kj} - m_{kj})q_k = (t_{ij} - m_{ij})q_i \quad (3.2)$$

Let m_{ij} be the per-unit cost of inputs if j is producing to supply i. Assume that $m_{ij} = m_i$ for all the sellers that could be trading with buyer i. Note that the seller pays no costs for linking and, everything else equal, its period payoffs are not directly affected by the quality of the match with its buyer.

3.3.2 The Network Formation Stage

In the first stage of the game, given $g^{\tau-1}$, last period's state, a set of links is opened for negotiation, generating $\tilde{g}$, the negotiation network. This is reached through all buyers choosing in a decentralized fashion at most one of the sellers available for supplying garment in that period.

More formally, each buyer i simultaneously announces at most one link to (re)negotiate. Let a_i denote actions available to buyer i and $a_i \in A_i$, which is the set of all the potential individual links to buyer i. i's announcement can involve linking to a player he is not linked to under the current state (proposing a new link), re-linking with its existing supplier or not trading at all: $\{1, \ldots, S, \emptyset\}$ so $|A_i| = S + 1$. Then, in a given period, each buyer negotiates with at most one seller[6].

[6]This restriction can easily be relaxed in the empirical application and has its theoretical generalisation in Lee and Fong (2013).

Before announcements are made, each i privately observes a period payoff shock to each action, $\epsilon_{a_i,i}$ so $\epsilon_i = \epsilon_{1,i}, \ldots, \epsilon_{|A_i|,i}$ independently drawn from a continuous $f_i^{\epsilon}(\epsilon_i)$. For simplicity, $f_i^{\epsilon}(\epsilon_i) = f^{\epsilon}(\epsilon_i)$ and while individual shocks are privately observed, f^{ϵ} is common knowledge. These are shocks to the payoffs i would make under each of the possible configurations $a_i \in A_i$. After privately observing her vector of shocks, i chooses a_i and announces it publicly.

In this context, the choice set for the buyers is the set of sellers (plus the no-link option). Each entry in the ϵ_i vector then constitutes a component that enters the per-period payoffs of i additively when linking with each seller and this is a) unobservable to the researcher, and b) unobservable to other buyers. Therefore, this captures all the aspects of the linking choice that are not present in the data (unobservable to the researcher) and that prevents other buyers from making a certain conjecture on rivals' choices (unobservable to other buyers). Note that this shock is drawn every period, so, coming from the same distribution, its value is time - buyer - seller (or action) specific. While g collects the common knowledge state variable, ϵ is the state variable collecting the private information component. Assuming additive separability of the action shocks, building on 3.1, the period payoffs including shocks are $\pi_i^b(g^{\tau}(a_i), \mathbf{t}) + \epsilon_{a_i,i}$ [7].

A negotiation network $\tilde{g}(\mathbf{a})$ is formed through all the links ij such that $ij \in a_i$ for all i. In other words, the negotiation network is formed only as a result of the non-coordinated announcements of the buyers. At this stage, sellers play no active role in the linking game and negotiations will take place in every pair nominated by the buyers, which describes more realistically the setting we are interested in. After all public announcements, all the players observe the negotiation network, $\tilde{g}(\mathbf{a})$.

While linking is costless for the sellers, each buyer i incurs a cost $c_i(\tilde{g}(\mathbf{a})|g^{\tau-1})$ for the renegotiation. We assume that all buyers incur the same fixed cost of linking with an existing supplier, $\underline{c}$, which is lower than the cost $\overline{c}$ of linking with a new seller. We assume away any cost of breaking existing links. Then, $c_i(g(\mathbf{a})|g^{\tau-1}) = \overline{c}\mathbf{I}\{ij \in a_i \textbf{ , } ij \notin g^{\tau-1}\} + \underline{c}(1 - \mathbf{I}\{ij \in a_i \textbf{ , } ij \in g^{\tau-1}\}$, and $\mathbf{I}\{\cdot\}$ is an indicator function that takes value one if the statement in the curly brackets holds true and takes value zero otherwise. Therefore, a pair that is already active in the network bears a low cost for linking, while starting a relation with a new supplier imposes a high cost in 3.1.

[7] This assumption is equivalent to **Assumption AS**, equation 3.5, in Rust (1994) and plays a role in the estimation approach in Chapter 4.

3.3.3 The Pricing Problem

Given $\tilde{g}$, the negotiation network, players bargain on prices under a standard Nash protocol[8]. Linking announcements being uncoordinated can lead to $\tilde{g}$'s for which some of the linked pairs exhibit no individual gains from trade, in which case no trade takes place and the corresponding link dissolves. In addition, the network formation protocol described above is compatible with negotiation networks in which sellers are linked to more than one buyer. However, the capacity constraints of the sellers restrict the possible networks to those that exhibit one-to-one links only. Call $O(\tilde{g}) = g'$ an operator mapping from the states space to itself, with g' being the network arising from $\tilde{g}$ after deleting all the links that exhibit no gains from trade for at least one of the players, within the constrains imposed on the network.

The gains from trade in this dynamic game include both the period profits, π, and the future discounted value of being in a given network, V. Per-period contracts $t_{ij;g'}$, between any linked pair under g' then satisfy the following *generic* condition:

$$\begin{aligned} & t_{ij;g'} \in argmax_{\tilde{t}}\big[[\pi_i^b(g', \tilde{\mathbf{t}}_{g'}) + \beta V_i^b(g')] - [\pi_i^b(g'', \mathbf{t}_{g''}^{\sigma}) + \beta V_i^b(g'')]\big]^{b_{ij}} \\ \times \quad & \big[[\pi_j^s(g', \tilde{\mathbf{t}}_{g'}) + \beta V_j^s(g')] - [\pi_j^s(g'', \mathbf{t}_{g''}^{\sigma}) + \beta V_j^s(g'')]\big]^{b_{ji}} \end{aligned} \tag{3.3}$$

The surplus for the buyer is defined as the difference in current and future payoffs between trading with the seller she is linked to or not doing so and b_{ij} and b_{ji} are the corresponding bargaining parameters, which naturally add up to one. In this context, Nash bargaining parameters equal to 0.5, for instance, give an equal division of the surplus. Setting $b_{ij} = 0$ gives the Nash-Bertrand pricing solution in the competition upstream.

The first term of the downstream player's surplus, $[\pi_i^b(g', \tilde{\mathbf{t}}_{g'}) + \beta V_i^b(g')]$, contains the relationship payoffs, with g' being the *stable* network arising after $\tilde{g}$ is formed and $\tilde{\mathbf{t}}_{g'} = \{\tilde{t}, \mathbf{t}_{-ij;g'}^{\sigma}\}$, with optimisation over $\tilde{t}$ taking all other prices, optimally determined, as given. The second term in the buyer's surplus in 3.3, $[\pi_i^b(g'', \mathbf{t}_{g''}^{\sigma}) + \beta V_i^b(g'')]$, contains the counterfactual payoffs for the buyer, if the relationship was broken. Let g'' be the counterfactual network and $\mathbf{t}_{g''}^{\sigma}$ its associated prices. Different assumptions on g'' and prices adjustments after disagreement imply alternative ways of endogenising the players outside options.

[8]For a detailed explanation, see Muthoo (1999).

As in Lee and Fong (2013), the pricing problem is *networked* in the sense that the surplus over which bilateral bargain takes place depends on other bilateral negotiations taking place in the graph. For games with one player only in one side, Hart and Tirole (1990); Horn and Wolinsky (1988); Segal and Whinston (2003) propose approaches that describe those interactions across simultaneous bilateral negotiations. Similarly, de Fontenay and Gans (2014) generalise the framework to two-sided large games. Like in Lee and Fong (2013), the pricing problem is as well *dynamic*: the framework captures the period effects of failed agreements together with the impact of disagreement in the continuation values V for the bargaining pairs. Finally, outside options are *endogenously determined*, as they are not given by a fixed counterfactual outcome but by the outcomes potentially reached under network-specific renegotiations and re-linking.

The framework in Lee and Fong (2013) defines g'' to be g'_{-ij}, equivalent to deleting link ij in network g' and $\mathbf{t}^{\sigma}_{g''} = \mathbf{t}^{\sigma}_{-ij,g'} = \{\mathbf{t}^{\sigma}_{g'} \setminus t^{\sigma}_{ij;g'}\}$, such that in the current period, a price for pair ij is not defined (as g'' does not include the pair) and the contracts between all other pairs remain unchanged. In other words, disagreement points imply that all the contracts that involve the rest of the players in the negotiation network are binding, so after i and j disagree, no contemporaneous changes in $\mathbf{t}_{g'-ij}$ are allowed for. This setup is consistent with the idea that bargaining takes place simultaneously for all linked pairs. As a consequence, other buyers who might have chosen supplier j under the new circumstance, cannot do so immediately and adjustments of this type will take time.

In the conceptualisation of Horn and Wolinsky (1988) this equilibrium can be interpreted as the Nash equilibrium across many Nash bargains. As explained in Crawford and Yurukoglu (2012), this is equivalent to considering a simultaneous moves game, where a player is conformed by a pair ij, whose strategy is $t_{ij,g'}$ and whose payoff is the Nash product of i and j's surpluses. Then, the bargaining problem is solved as the Nash equilibrium of that game. Such a device rules out the possibility of a player exploiting an informational asymmetry due to the order in which negotiations take place. So, if j is bargaining at the same time with buyers i and k, j has no information advantage about the outcome of the process with k when bargaining with i and viceversa.

Given the simultaneity in all the bargains and the fact that disagreements are off-equilibrium events, Lee and Fong (2013) leave prices for all other pairs fixed upon disagreement in the current period. An alternative specification would be to define g'' to be the network that arises after deleting ij from g', allowing for all the pairs to renegotiate prices in the new setting, closer to the non-binding contracts setting described in Stole and Zweibel (1996). This is the alternative I propose here. To observe the difference this approach makes in the generation of disagreement points a small static example is presented in Appendix H. In short, consider a seller that is bargaining simultaneously with two buyers of which he will choose one. One possibility would be that when bargaining with the first buyer, the disagreement payoffs of the seller were those of trading with second buyer at the price this could agree to pay under the current situation. But actually, if the seller was to break the link with the first buyer, the conditions in which she would bargain with the second buyer are those in which the seller's outside option was not trading at all.

Given the per-period profits defined in 3.1, the gains for buyer i from trading with j depend on the continuation values for $V(g')$ and $V(g'')$, on the negotiated t_{ij} and an outside price for the garment, $x_{g''} = x$ [9].

$$S^b_{ij}(g') = [(-t_{ij}(g') + x_{g''} + \rho_{ij})q_i + \beta(V^b_i(g') - V^b_i(g''))] \tag{3.4}$$

While each buyer negotiates with at most one seller in any network, as a result of the uncoordinated linking decisions in the first stage, sellers might participate of multiple simultaneous bargains at a given point in time. Given the sellers' (capacity) constrains to trade with one buyer only, using 3.2, the gains from trade for seller j when bargaining with buyer i under network g' is given by:

$$\begin{aligned} S^s_{ij}(g') = (t_{ij}(g') - m_i)q_i + \beta V^s_j(g') - \max_{k\in\overline{B},k\neq i} \\ \{[g'^{(kj)}_{kj} \times [(t_{kj}(g'^{(kj)}) - m_k)q_k + \beta V^s_j(g'^{(kj)})]] \ , \\ \beta V^s_j(g'^{(\emptyset j)})\} \end{aligned} \tag{3.5}$$

In some abuse of notation, $g'^{(kj)} = g'_{-ij} \setminus \{nj : g'_{nj} = 1, n \neq k\}$, so the outside option for seller j negotiating with buyer i is the best over the alternative partners she has under g' or not trading in the current period at all.

3.3.4 The Dynamic Specification

The system evolves with g^τ following a Markov process with known transition $P(g^{\tau+1}|g^\tau, \mathbf{a}^\tau)$. Assume conditional independence of the transitions between states, such that $P(g_{t+1}, \epsilon_{t+1}|g_t, \epsilon_t, a_t) = f_\epsilon(\epsilon_{t+1})CDF_g(g_{t+1}|g_t, a_t)$, with $f_\epsilon(\cdot)$ with finite first moment,

[9] An alternative specification that was explored defined the outside price for the buyer as depending on the number of available (*unlinked*) sellers in the counterfactual network, following $x_{g''} = \kappa(S - \sum_k^B \sum_j^S g''_{kj})^{\frac{-1}{2}}$, with κ a constant.

continuous and differentiable twice. Note then that ϵ^τ affects the transition across states g only via the choices of actions a, but not directly [10].

A Markov strategy for buyer i constitutes a mapping $\sigma_i(g, \epsilon_i) : \mathbf{G} \times \mathbf{R}^{|A_i|} \to A_i$ so the buyer only observes the current network, or *state*, and its individual draw of action-specific shocks to choose a_i. Note that only the current state is relevant in the mapping. Consider stationary strategies only, such that i's decision is the same in t and s, whenever $\{g^t, \epsilon_i^t\} = \{g^s, \epsilon_i^s\}$.

In this setting, the conditional choice probability of action a_i being chosen by i, when the state of the world is g is given by:

$$P_i^\sigma(a_i|g) = Prob(\sigma_i(g, \epsilon_i) = a_i) \int \mathbf{I}\{\sigma_i(g, \epsilon_i) = a_i\} f^\epsilon(\epsilon_i) d\epsilon_i \tag{3.6}$$

where $\mathbf{I}$ is an indicator taking value one when the argument holds true and we integrate over all the possible ϵ_i's. By 3.6, the probability of agent i announcing a_i depends on the current network and ϵ_i, which is not observed by third parties. Therefore, P_i^σ constitutes the probability that an agent different from i attaches to i choosing a_i and it is then the belief that a third party has on i's choices (Aguirregabiria and Mira, 2007).

With independent draws of ϵ and conditional on her own action, the probability that agent i assigns to the final negotiation network being g', given that the observable state is g and other players's strategies are σ is just the product of the corresponding P_k^σ's:

$$\varrho_i^\sigma(g'|a_i, g) = \sum_{a_{-i} \in \prod_{k \neq i} A_k} \Big(\prod_{k \neq i} P_k^\sigma(a_{-i}[k]|g) \Big) \mathbf{I}\{\tilde{g}(a_i, a_{-i}) = g'\} \tag{3.7}$$

where a_{-i} is a vector containing actions a_k of all the players $k \neq i$ and $a{-}i[k]$ is the k^{th} action in that vector. So the probability that i attaches to network g' arising is just: (i) the sum over all the possible vectors collecting actions a_k for all the players $k \neq i$ (which amounts to all the possible combinations of the elements in the A_k sets, so the product of these); (ii) of the product over all the k's of the probabilities that i assigns to each agent $k \neq i$ playing action a_k in the vector a_{-i}, whenever the actions in a_{-i} together with action a_i result in network g'.

Denote with $c_i(g'|g)$ the linking cost for i when the starting state is g and i's choice corresponds to network g'. Let $O(.)$ be the mapping defined above, such that whenever a network is proposed a new network eventually arises after all unstable links in the proposed network have been broken. Defining $v_i^\sigma(a_i, g)$ as the current and future profits

[10] This is **Assumption CI** in Rust (1994).

net of the stochastic utility component, ϵ, if i chooses action a_i when the state is g and he behaves optimally in the future, we have in 3.8 the *choice-specific value function*:

$$v_i^\sigma(a_i, g) = \sum_{g'} \varrho_i^\sigma(g'|a_i, g)(c_i(g'|g) + [\pi_i^b(g'', \mathbf{t}_{g''}^\sigma) + \beta V_i(g'') : g'' = O(g', V^\sigma)]) \quad (3.8)$$

So the value for player i of choosing action a_i is the sum of current and future payoffs he would make under the different negotiation networks g' compatible with action a_i, weighted by the probability i attaches to each of these g' arising, conditional on the current state g and the chosen action. The current and future payoffs are then given by the cost from negotiating network g' plus the expected payoffs, current and future, attained under the stable network that arises from negotiation network g'.

At each state g, the corresponding value function (the *integrated Bellman equation*) is defined as:

$$V_i^\sigma(g) = \int [max_{a_i \in A_i}(\epsilon_{a_i,i} + v_i^\sigma(a_i, g))] f^\epsilon(\epsilon_i) d\epsilon_i \quad (3.9)$$

which represents i's current and future profits at the beginning of each period, before the ϵ's are drawn, given that the state network is g and everybody is playing strategies according to σ_{-i}.

Note that under the assumptions of additive separability of the private information component in the players payoff functions and the conditional independence of the transitions between states, the dynamic programming problem is fully characterised by the Bellman equation in 3.9, which in turn is analogous to a static discrete choice problem, with choice specific (intertemporal) values instead of period profits (Rust, 1994).

For a fixed set of payoffs $\{\pi(\cdot)\}$ the equation above is a contraction mapping and has a unique V_i^σ that solves it for any given σ , under the assumptions of finiteness of the state space and the restrictions imposed on the error term and its relation to stage profits (Aguirregabiria and Mira, 2002).

3.3.5 Markov Perfect Equilibria

Consider the pure strategy Markov Perfect Equilibrium of the game to be a set of strategies σ^* such that for any i, network g and shocks ϵ_i:

$$\sigma_i^*(g, \epsilon_i) = argmax_{a_i \in A_i}[\epsilon_{a_i,i} + v_i^{\sigma^*}(a_i, g)] \tag{3.10}$$

, where the restrictions in the price bargaining problem and stability of the network are satisfied: so given V^{σ^*}, period contracts $\mathbf{t}_g^{\sigma^*}$ satisfy the Nash problem in 3.3, with 3.4 and 3.5 defining players' surplus for all stable g[11] [12].

It can be seen that a strategy profile σ is Markov Perfect if there is no player i and alternative strategy σ_i' such that player i prefers σ_i' over σ_i, when all other players are playing σ_{-i}. This is, $\forall i$,$\forall g$ and $\forall \sigma_i'$ alternative strategies: $V_i^\sigma(g, \epsilon_i|\sigma_i, \sigma_{-i}) \geq V_i^\sigma(g, \epsilon_i|\sigma_i', \sigma_{-i})$. The reader is referred to Maskin and Tirole's original paper for definitions and proofs (Maskin and Tirole, 1988). Intuitively, this equilibrium concept implies (i) that for each state of the world, optimal policies are chosen by all players given their beliefs on the future structure of the network and (ii) that those beliefs are consistent with rivals' behaviour.

Lee and Fong (2013) argue that the above can be re-written in the space of probabilities, following the procedures in the work by Aguirregabiria and Mira (2002). With P^{σ^*}, the conditional probability corresponding to the MPE σ^*, an analogous fixed point of the best response probability function describes the solution of the system. To re-express the problem in the space of probabilities, note that π_i, V_i and $\varrho_i(g'|g, a_i)$ depend on players' strategies only through P_i, the associated probabilities. Also, by the definition of P_i and σ^*, $P_i^*(a_i|g) = \int \mathbf{I}\{a_i = \sigma_i^*(g, \epsilon_i)\} f_i^\epsilon(\epsilon_i) d\epsilon_i$, so equilibrium probabilities are a fixed point $\Lambda(P^*) = P^*$ with

$$\Lambda_i(a_i|g; P_{-i}) = \int \mathbf{I}\{a_i = argmax_{a \in A_i}(\epsilon_{a,i} + v_i^{P^*}(a, g))\} f_i^\epsilon(\epsilon_i) d\epsilon_i \tag{3.11}$$

with v^P being choice specific value functions derived from v^σ and defined in terms of conditional choice probabilities P^*. In the terms of Aguirregabiria and Mira (2007), Λ_i constitutes the *best response probability function* for agent i and it is continuous (given the assumptions on f_ϵ) in the choice set, so that existence is guaranteed by Brower's Theorem. Under standard regularity conditions, existence in this type of game with dynamic strategic interaction and incomplete information is guaranteed (Aguirregabiria

[11]Buyers and sellers interactions over the infinite horizon could induce several complex behavioural patterns compatible with other equilibrium concepts, like more unrestricted concepts of subgame perfection. I follow the literature in restricting attention to Markov Perfect Equilibria in pure strategies (which in turn, in our context is also subgame perfect).

[12]The focus on pure-strategy equilibria only follows Aguirregabiria and Mira's argument, according to which a mixed strategy equilibrium in a complete information game can be interpreted as a pure strategy in the game with incomplete information, such that the probability distribution of players' actions is the same under the two equilibria, as shown in Harsanyi's "Purification Theorem" (1973) (Aguirregabiria and Mira, 2007).

and Mira, 2007; Doraszelski and Satterthwaite, 2010). More specifically, following Aguirregabiria and Mira (2007) to prove existence, at least one fixed point of the mapping is to be found. This, in turn implies showing that the mapping is continuous in the compact space of probabilities. It is sufficient to show that the choice-specific value functions are continuous in P for all g. This will follow from the shape of the per-period function, uniqueness in the pricing problem, continuity of prices on P and continuity of π in prices [13].

For the purpose of this paper, as in many other applications of models of industry dynamics for empirical estimations, the discussions around existence is two-fold (Doraszelski and Pakes, 2007): one aspect of it, is connected to whether the computation algorithms that find an equilibrium, sometimes required for estimation purposes, actually converge to policies that satisfy, with error, the equilibrium conditions of the model; the second aspect is whether such conditions are guaranteed to hold exactly under the assumptions of the model. With regards to the former, most papers exploiting iterative algorithms to find MPE do converge, even when the proved *sufficient* conditions for existence are not satisfied (Ackerberg et al., 2007). Regarding the latter, starting from the general framework in Ericson and Pakes (1995), various assumptions have been presented to guarantee existence in the context of specific applications, ranging from allowing for mixed strategies to the more widespread alternative of introducing incomplete information, for example, as firm-specific privately known scrap values or entry costs (Doraszelski and Pakes, 2007; Doraszelski and Satterthwaite, 2010; Ericson and Pakes, 1995). Lee and Fong's existence assumption (A.3.1. in their paper) involves allowing for a buyer - seller shock after the negotiation network is formed, drawn independently over time and all players from a known distribution with full support, such that small changes in conditional choice probabilities don't trigger discontinuous jumps in the choice specific value functions. In their application, however, their algorithm converges to an equilibrium when those shocks are assumed away. The computer exercises in section 3.4 show that this is also the case for the game presented here.

For arbitrary parameters, multiple equilibria is likely to arise in our context, as in most games of the same class with best responses being non-linear functions of rivals' actions. A discussion of additional assumptions that have been imposed to guarantee uniqueness in similar games can be found in Doraszelski and Pakes (2007). However, these are not applicable to our setting over the whole of the parameters space and I will need to return to multiplicity issues when estimating the game.

[13] And in our context, given the value functions, this simplifies to a system of linear equations, in which the price enters linearly in profits of the parties

3.4 Computation of Equilibria

Given probabilities P, solving for the equilibrium/a defined above, would either require finding a solution to the B dynamic programming problems defined by $V_i^\sigma(g)$, and finding the corresponding equilibrium probabilities via 3.11 or exploiting Hotz and Miller's (1993) invertibility approach, following (Aguirregabiria and Mira, 2007).

Using stars for the MPE equilibrium, the associated transition probabilities and the equilibrium value functions for all agents, σ^*, P^*, $\{V_i^{P^*}\}$, the Bellman expression $V_i^\sigma(g)$ in equilibrium, implies:

$$V_i^{P^*}(g) = \sum_{a_i \in A_i} P_i^*(a_i|g)[\tilde{\pi}_i^{P^*}(a_i|g) + e_i^{P^*}(a_i, g)] + \beta \sum_{g'} V_i^{P^*}(g')\overline{\varrho}^{P^*}(g'|g) \tag{3.12}$$

where $\tilde{\pi}$ is i's expected period profit including the costs c_i from choosing action a_i,

$$\tilde{\pi}_i^{P^*}(a_i|g) = \sum_{g'} \varrho^{P^*}(g'|a_i, g)[c_i(g'|g) + \pi_i(O(g'), \mathbf{t}_{O(g')}^{P^*})] \tag{3.13}$$

$\overline{\varrho}^{P^*}$ are the induced transition probabilities between states g' and g, summing up over actions on $\varrho_i^\sigma(g'|a_i, g)$ in 3.7:

$$\overline{\varrho}^{P^*}(g'|g) = \sum_{\mathbf{a} \in \prod_k A_k} \prod_{j=1}^{N} P_j^*(\mathbf{a}[j]|g)\mathbf{I}\{O(\tilde{g}(\mathbf{a}), V^{P^*}) = g'\} \tag{3.14}$$

and $e_i^{P^*}$ is the expected choice specific payoff shock to agent i choosing a_i:

$$e_i^{P^*}(a_i, g) = E[\epsilon_{a_i,i}|\sigma_i^*(g, \epsilon_i) = a_i] = \int \epsilon_i \mathbf{I}\{\sigma_i^*(g, \epsilon_i) = a_i\} f_i(\epsilon_i) d\epsilon_i \tag{3.15}$$

Note that $E(\epsilon_{a_i,i}|g, \sigma_i^*(g, \epsilon_i) = a_i)$ is a function of a_i, P^* and f_ϵ. As $\{\sigma_i^*(g, \epsilon_i) = a_i\}$ is only true when $\{v_i^{P^*}(a_i, g) + \epsilon_i(a_i) \geq v_i^{P^*}(a, g) + \epsilon_i(a)\text{for any } a \neq a_i\}$ which means:

$$e_i^{P^*}(a_i, g) = \frac{1}{P_i^*(a_i|g)} \times \int \epsilon_i(a_i)\mathbf{I}\{\epsilon_i(a) - \epsilon_i(a_i) \leq v_i^{P^*}(a_i, g) - v_i^{P^*}(a, g) \quad \forall a \neq a_i\} f_i(\epsilon_i) d\epsilon_i \tag{3.16}$$

It can be seen then that $e_i^{P^*}$ depends only on f_ϵ and value differences $\tilde{v}_i^{P^*}(g) = \{v_i^{P^*}(a, g) - v_i^{P^*}(0, g) : a \in A\}$. Likewise P^* is a function of f_ϵ and the $\tilde{v}$: $P_i^*(a_i|g) = Prob\{\epsilon_i(a) - \epsilon_i(a_i) \leq v_i^{P^*}(a_i, g) - v_i^{P^*}(a, g) \quad \forall a \neq a_i|g\}$.

The first proposition in Hotz and Miller establishes that the mapping from value differences to probabilities is invertible and then e_i is a function of P^* and f_ϵ only (1993). The value function above can be then written in matrix notation, for the vector of $V_i^{P^*}$ across all network states g as follows:

$$\mathbf{V}_i^{P^*} = (\mathbf{I} - \beta_i \overline{\varrho}^{P^*})^{-1} (\sum_{a_i \in A_i} \mathbf{P}_i^*(a_i) * [\tilde{\pi}_i^{P^*}(a_i) + \mathbf{e}_i^{P^*}(a_i)]) \tag{3.17}$$

where $\mathbf{I}$ is the identity matrix of size $|G| \times |G|$, $\overline{\varrho}$ is the matrix of transition probabilities from g to g' for all possible g, so it has size $|G| \times |G|$, $\mathbf{P}$ collects the probabilities for i of choosing action a_i conditional on each possible network g ($|G| \times 1$), multiplied element-wise by the profits under action a_i, for each possible g configuration. So, given P^*, the above expression gives the expected value for player i in a given state g if all the players behave currently and in the future according to the choice probabilities P^*.

Let $\boldsymbol{\Upsilon}_i(P) = \{\Upsilon_i(g, P) : g \in \mathbf{G}\}$ be the solution to 3.17 given P, this is, the expected (current and future) profits for i when all players behave following P. Aguirregabiria and Mira show that a fixed point in the following mapping is also a fixed point in de Λ problem above, 3.11, and is then an MPE of the original game (Aguirregabiria and Mira, 2007) [14]:

$$\Psi_i(a_i|g; P) = \int \mathbf{I}\{a_i = argmax_{a \in A_i}(\epsilon_{a,i} + \tilde{\pi}_i^P(a, g) + \beta_i \sum_{g'} \Upsilon_i(O(g'; \boldsymbol{\Upsilon}(P)), P) \varrho_i^P(g'|a, g))\} f_i(\epsilon_i) d\epsilon_i \tag{3.18}$$

The main advantage of this representation in terms of the practical computation of the MPE of our game is immediate: the Λ problem in 3.11 does not take future actions as given, so to evaluate the function for a given agent, the implicit dynamic programming problem needs to be solved. The Ψ problem in 3.18, instead, takes future actions as given, via the Υ definition, so it reduces to a system of linear equations.

On this basis, a computation algorithm is developed by Lee and Fong (2013). The following subsection presents an adaptation of Lee and Fong's algorithm to our setting and describes its implementation in the context of a specific exercise that will inform that predictions of our model.

[14] The Representation Lemma in Aguirregabiria and Mira's paper establishes the equivalence of the fixed points sets across the two mappings (Aguirregabiria and Mira, 2007). Early contributions in Berry (1994) and Berry et al. (1995) prove uniqueness of the solution of an equivalent inversion problem and properties of the contraction.

3.4.1 The computation algorithm

Various algorithms have been suggested to compute Markov Perfect Equilibria [15]. The one proposed here follows the broad structure in the seminal work by Pakes and McGuire (1994): each iteration has a starting value, that is updated according to the equilibrium conditions of the game, the "distance" between the updated value and the starting value is evaluated and if these are not close enough, according to a pre-specified cutoff, a new iteration starts with the updated values as new starting points. Updating occurs at every possible state of the world and for every point in the policy and value functions. The starting functions in each iteration (either a guess for the fist iteration or last round's updated result) governing players' behaviour and transitions over states are taken as the *true* policies for rival firms and transitions, so updating value functions for each player constitutes a single-agent dynamic programming problem. The most suitable cutoff, naturally, depends on the implemented algorithm.

Unlike most of the applications of algorithms computing MPE of similar games, the *networked* structure of the game proposed here implies that the profit functions cannot be computed *off-line* and fed into the algorithm. Instead, because the equilibrium prices depend on future values, which in turn depend on equilibrium prices, prices and stage profits would need updating within each iteration as well. Within this structure, Lee and Fong propose an iterative procedure that, applied to our setting, can be informally described by the steps below.

Consider the profit equations for buyers and sellers, as described by equations 3.1 and 3.2. Start by fixing the exogenous components of the model: the size of the game, B and S; prices of inputs, $\{m_i\}$, final prices in the buyers' domestic markets, $\{r_i\}$, and each buyer's demand, $\{q_i\}$; and the (exogenous) outside price for the buyers $x_i = x$. Choose a suitable set of parameters for the game: costs of linking, $\underline{c}$ and $\bar{c}$; bargaining parameters, b_{ij} for all players i and j; and matching qualities ρ_{ij} for all players i and j.

1. Start with an initial guess of conditional choice probabilities, P^0 of size $B \times |A_i| \times |G|$, period contracts, $\mathbf{t}^{P^0}$ of size $B \times S \times |G|$, and value functions $\mathbf{V}^{P^0}$ of size $(B + S) \times |G|$[16].

2. Start the following iteration procedure until convergence:

[15] In the brief comments here I exclude algorithms that re-express the problem as a system of non-linear equations and solve for it, as for large games like the one at hand, the advantages of Gaussian methods have been discussed extensively (Doraszelski and Pakes, 2007; Pakes and McGuire, 1994)

[16] The procedure presented in the next subsection has been run initialising the algorithm with random CCPs, prices and values, as well as arbitrarily fixed arrays. Convergence is achieved in the relevant areas of the parameter space irrespective of the initialisation

(a) Use CCPs to construct the transition matrix for states $\overline{\varrho}^P(g'|g)$ and the conditional transitions, $\varrho_i^\sigma(g'|a_i, g)$, for every action, player and state.

(b) Given $\mathbf{t}^P$ and $\mathbf{V}^P$ find the sellers' best response to each possible negotiation network, this is, out of all the buyers linked to the seller under a given network, identify the relationship that gives largest payoffs - treat no-linking as an alternative.

(c) Compute players period payoffs under each possible network in all standing bilateral relations.

(d) Use the state transitions and the period payoffs of the standing relations for each player to generate the value functions. For simplicity, I perform this via value function iteration.

(e) For each negotiation network (both standing and non-standing relations) compute the outside options for each player in each bilateral negotiation she faces, taking all other prices as given, using the value functions computed above.

(f) Given the bargaining parameters, for each linked pair solve the Nash Bargaining problem to obtain prices. All pairs that exhibit no gains from trade for at least one of the parties in trade are unstable. Note that in our context, the simultaneous Nash Bargaining problems reduce to a system of (simultaneous) linear equations.

(g) Update the CCPs for each buyer. In my application, I assume ϵ follows a Type I Extreme Value distribution, which makes the updating stage straightforward, obtaining CCPs as ratios of transformed inter-temporal profits [17].

(h) Feed in the CCPs updated in $(2.g)$ and the prices and stability rule obtained in $(2.f)$ to start a new iteration in $(2.a)$.

3. Perform step (2) until convergence is achieved. In Lee and Fong convergence is evaluated element-wise as $|\mathbf{V}^{P^{\tau+1}} - \mathbf{V}^{P^{\tau}}| < \omega$ with ω pre-specified, with τ denoting iterations of step (2) (Lee and Fong, 2013). I set $\omega = 10^{(-6)}\frac{1}{1+|V^{\tau}|}$ which is equivalent to using the sup-norm criterion discussed in Doraszelski and Pakes (2007) [18].

The algorithm proposed here (again, following Lee and Fong (2013)) is not a contraction mapping so convergence is not guaranteed. Moreover, like in Pakes and McGuire

[17]The convenience of this parametric choice for computational purposes is immediate. The criticism around the Independence of Irrelevant Alternatives observed early in Debreu (1960), does not hold in the dynamic context, as the choice specific value functions depend on all other alternatives via future payoffs, even when the stage profits are a function of the (one) current action only.

[18]For robustness, the smaller exercises were run twice, once evaluating convergence on the values and once evaluating convergence on the CCPs. No differences in the equilibrium reached were found, although the convergence in CCPs was found less smooth (reasonably enough in the context of our application) and slower, as the sup norm is evaluated over larger arrays: CCPs are player, action and state specific.

(1994) systematic non-convergence and cycling can arise due to the characteristics of the game. Like in the classic entry-exit example, choices in the linking stage are such that discontinuities in future values can arise, particularly when more than one buyer *clump* choosing the same seller, bringing the future values discontinuously down for (some of the) buyer(s) causing the corresponding links to break inducing another discontinuous jump in values. One way of solving this is introducing additional randomness in the linking stage. A second issue inducing cycling patterns in the convergence path is a non-uniqueness feature immediately associated to the specification of the game: consider two buyers linking with one seller ($g_{ij} = g_{kj} = 1$); in the game presented here, there are occasions in which either of the links could be individually sustainable provided the other link breaks, and an iteration starting with both firms linking, can induce a best response of none of them linking, so each buyer would hold the belief that the rival is not linking, and insist herself on re-forming the link, going back to the starting point. One possible way of solving this type of cycling pattern is to introduce an ordering in which the breakage occurs (in line with Pakes and McGuire's type of solution). This is, indeed, naturally embedded in our game. In the presence of enough heterogeneity affecting the surplus each seller makes with each individual link, only the link with higher surplus is kept. A random device picks out one link only in the unlikely case of a tie occurring.

3.4.2 Realising Equilibria of a Small Game

A number of challenges, from the perspective of the computation of an equilibrium, remain to be tackled. The first one is the size of the state space. Even in our application, where each buyer chooses to link with one seller only and the equilibrium networks can only feature one-to-one relations, as the set of players grows large tractability can become an issue. The second one is the set of limitations in the uses of these kinds of models in the presence of potentially multiple equilibria.

This subsection presents the results of a procedure that *scans* the space of parameters for given primitives of the game, as a basis for discussing those challenges [19]. This implies defining a grid for each scalar parameter and computing an MPE of the game for each possible combination of parameters, following the algorithm proposed in the previous section. The main focus in this subsection is on the pattern of convergence and computation times and I leave the discussions around the characterisation of equilibria of the game for section 3.5.

For the sake of the computer exercise, the primitives of the game are as follows. Consider one market with two buyers and two sellers only, so $B = S = 2$, indexed $i = 1, 2$ and

[19] The Matlab code that implements the algorithm described above is available upon request, as well as the procedures that run the parameter sweeping and graphs.

$j = 1, 2$. Let the players' profit functions be defined by 3.1 and 3.2, with $m_i = m$, $q_i = q$ and $r_i = r$ and x exogenously determined, so buyers are symmetric in terms of the size of their demand, their revenues in their domestic markets and the quality (or price) of the inputs they require. Also, assume $b_{ij} = b_i$, so the bargaining powers are buyer-specific. To simplify the scanning exercise, fix the bargaining parameter for buyer 1, $b_1 = 0.5$, the cost of re-linking with an existing supplier, $\underline{c} > 0$, and the quality of the matches for buyer 1, such that $\rho_{11} > \rho_{12} = 0$. The remaining free parameters of the game are b_2, $\bar{c}$, ρ_{21} and ρ_{22}, which are scanned on reasonably fine grids [20].

Size of the Game and Computation Time. The following describes the time it takes to run through the first two iterations of the MPE algorithm, for a fixed vector of parameters, for different sizes of the game (combinations of total number of buyers and sellers). Time is measured in seconds and corresponds to a full run over the first two iterations, irrespective of the convergence path. On top of the additional time required to complete each iteration in larger games, the number of iterations until convergence could also grow with the size of the game, depending on the parameters, as a larger array needs to converge element-wise[21].

In our specification, the set of possible states has cardinality $(S+1)^B$. While a small game of size 2×2 gives only 9 possible states of the world, a slightly bigger market, with, for instance, 5 buyers and 5 sellers, gives $7,776$ states. This in turn, requires the computation of more than 77 thousand player-state values and $233,280$ conditional choice probabilities.

The table below shows that the first two iterations of the algorithm in a 2×2 game takes 0.09 seconds, while on the bottom-right corner, a 4×8 game takes more than $40,000$ seconds, which is around 11 hours of computer time. While improvements in the coding of the algorithm are possible to reduce computation times, this exercise shows that, convergence aside, the number of players and consequently the size of the state space can very quickly turn the computation of an equilibrium of the game unmanageable [22].

[20] Several versions of this parameter sweeping have been performed. The scanned grids for the largest exercise explored b_2 in 0.05 increments over the interval $[0, 1]$, $\bar{c} \in [\underline{c} = 0.5, 20.5]$, and both $\rho_{2j} \in [0, 4]$ for $j = 1, 2$ in 0.25 increments. This gives a result of $66,000+$ parameter vectors.

[21] The computation time corresponds to an iMac running on OS X Version 10.9.3, processor 3.5 GHz Intel Core i7, 32GB 16000 MHz DDR3, with four cores available but only one under use in Matlab R2013b.

[22] Section 5 in Doraszelski and Pakes (2007) presents an excellent review of methods that could potentially alleviate the dimensionality problem referred here.

TABLE 3.1: Computation Times for Different Sizes of the Game

	Buyers		
Sellers	2	3	4
2	0.09	0.24	2.11
3	0.12	1.35	25.44
4	0.24	5.91	191.55
5	0.52	20.37	1,019.50
6	1.03	60.29	4,156.10
7	1.89	160.91	15,362.00
8	3.23	357.74	40,683.00

Non-Convergence. In the largest parameter sweep, of the $66,910$ different vectors of parameters, 61.02% of them produce an equilibrium within the maximum number of iterations. In the largest exercise, for computational purposes the maximum number of iterations was dropped down to 500. While smaller experiments were run with up to $5,000$ iterations, convergence occurs most of the times within the first 30 iterations. The convergence cutoff in all the exercises was $10^{-6} \times (|1 + \mathbf{V}|)^{-1}$. The parameters in the remaining 39% of the runs can be divided into two groups. One group, accounting for 27.14% of the set of all the parameters, correspond to computations in which the CCPs (and values) would visit cyclically a fixed set of points. The length of the cycle varied from 2 to 5 points, with median and mean close to 2. The observed cycles occurred in areas of the parameter space that suggest traps like those described in sub-section 3.4.1: those presumably generated by low heterogeneity and non-uniqueness and those for whom changes in the discrete decision of linking would induce non-smooth jumps in opponents' values.

In smaller experiments, procedures to address cycle traps in iterative algorithms were performed (mainly, re-starting the iterations with a convex combination of the nodes in the cycle), with success in some areas of the parameter space. The remaining (almost) 12% of the vectors of parameters did not converge to an equilibrium within the maximum number of iterations nor it converged to an absorbent cycle (of length smaller than or equal to the size of the state space). The results in the rest of this chapter are drawn, except otherwise stated, on the $40,000+$ vectors that produced an equilibrium. Further work can be done to improve on the convergence rate over the rest of the parameters space. Of the converging parameters, 98.17% of the cases, attain convergence within the first 30 iterations and in an average close to 10 iterations.

Smoothness of Convergence. The algorithm described above is not a contraction mapping, so the convergence parameter (this is, the sup norm over all entries in the Value array across two consecutive iterations) is not necessarily monotonically decreasing over the iterations path. In our 2×2 setting, again, I fix the parameter vector and compute an equilibrium of the game for 50 different initializations of the CCPs. These include assuming constant probabilities over all actions, spaces and players and random draws from the uniform and normal distributions, starting on different seeds. The line graphs below show the convergence (to the same equilibrium) path over the first iterations, for three of the initialisations (arbitrarily chosen).

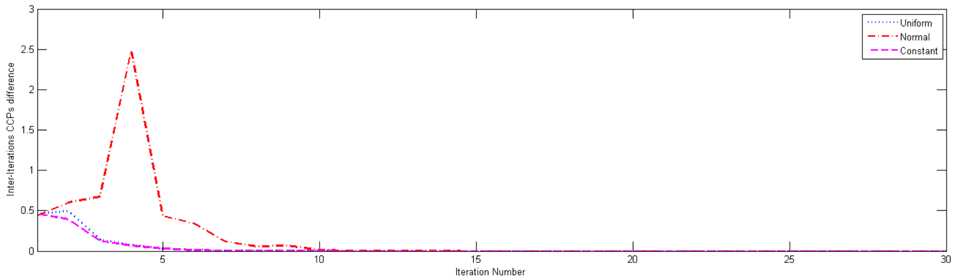


FIGURE 3.1: Convergence Path for Alternative Initialisations

Different parameter choices produce graphs in which the iteration path takes positive slope more than once. Papers using related algorithms present similar patterns of local-only contractions (Aguirregabiria and Mira, 2007; Pakes and McGuire, 1994).

Non-uniqueness. As stated above, the game proposed here in its general form and with no restrictions on the parameters is likely to produce multiple equilibria. Methods based on structures exploiting homotopic conditions have been used in applied papers to trace multiple equilibria. This is considered out of the scope of this chapter and I will limit the considerations on multiplicity to the relatively ad-hoc (and also quite wide-spread) practice of re-computing equilibria multiple times varying the starting conditions for a fixed parameter vector. Although the results in the table below in no way support a claim on uniqueness, they show some robustness in the convergence towards the same equilibrium or, in other terms, consistency in the selection mechanism in the presence of multiple equilibria, for a choice of parameters [23]. It is clear that in the context of the game we propose we can construct cases in which multiplicity arises immediately: lack of heterogeneity in the matching qualities and bargaining powers are compatible with more than one equilibrium. If, for each buyer the gains from trade are the same with both sellers, then at least two networks can arise as steady states: one in which $g_{11} = g_{22} = 1$ and one in which $g_{12} = g_{21} = 1$. Given the restrictions in the model, networks involving both buyers linking with the same seller cannot be stable and, for the low outside options set for the buyers, not trading is never a solution. Higher costs of linking will only induce heavier persistence on the initial linking choices, but these

[23] Note then that the choice of parameter vector is arbitrary and there is no theoretical reason for the results presented here to hold over the whole of the parameter space.

will be equally likely in this example. This case corresponds to the first line of the table, labeled as *Constructed Multiplicity*.

Before going into further detail, note that the table below has been produced with only $5,000$ computations of MPE for each selected vector of parameters. Smaller exercises have been performed with up to $10,000$ replications, finding non-significant qualitative differences with what is presented below.

The first column in the table shows the average number of iterations of the MPE algorithm until convergence, followed by its standard deviation. In the third column, I present the proportion of iterations that reached network $g_{11} = g_{22} = 1$, labeled as *Equilibrium 1* below, as the state that occurs with probability close to one in the steady state distribution over networks. For these cases, column four presents the average probability of network $g_{11} = g_{22} = 1$ [24]. To facilitate the discussion here, the parameters are chosen in a range such that networks in which not all of the players are trading do not arise in equilibrium. The possible steady state distribution over networks can give network $g_{11} = g_{22} = 1$ occurring with probability close to one, or $g_{12} = g_{21} = 1$ with equally high probability or a combination of both networks. Therefore, we only need to report the probability of one of these happening. The final columns show the average price and average value for buyer 1 when network $g_{11} = g_{22} = 1$ arises, accompanied by their respective standard deviations [25].

For the sake of our informal discussion on multiplicity, it can be seen that the amount of heterogeneity introduced in the game, via the quality of the matches and the bargaining parameters, is directly linked with the convergence towards one single equilibrium [26]. As described above, the extreme case is the one in the first row of the table. In this case, only 51% of the iterations fall in the *Equilibrium 1* with buyer 1 trading with seller 1 and buyer 2 trading with seller 2, with probability close to 1 as the steady network. The other half of the runs converge to the second possible equilibrium under these conditions: one in which $g_{12} = g_{21} = 1$ happens almost surely, while $P(g_{11} = g_{22} = 1)$ is close to zero under the steady state distribution over networks. As stronger heterogeneity is introduced both through ρ's and bargaining powers (cases 4, 5, 6, 8), one equilibrium of the two is picked in the majority of the runs.

[24] Standard errors are zero up to the 10^{-16}th decimal place and is then not reported here.

[25] Parameters for each case are set as follows: 1) $\rho_{11} = \rho_{21}$, $\rho_{12} = \rho_{22}$, $b_1 = b_2$, $\underline{c} = \overline{c}$, although same distribution over states is recovered with $\underline{c} < \overline{c}$; 2) as in case 1, except from $\rho_{21} = 0$ and $\rho_{22} = 10^{-3}$; 3) as in case 2, but with large costs of linking: $\overline{c} = 10 \times \underline{c}$; 4) as in case 1, except from $\rho_{21} = 10^{-3}$ which implies $\rho_{21} < \rho_{11}$ and $\rho_{22} = 10$ which implies $\rho_{22} > \rho_{12}$; 5) as in case 3, but with large costs of linking: $\overline{c} = 10 \times \underline{c}$; 6) and 7) as in case 1 but with $\rho_{22} = 2 \times \rho_{11}$, $\rho_{12} = \rho_{22}$ with and without advantage to buyer 2; 8) as in case 4, but now $b_1 = 0.8$ while $b_2 = 0.5$.

[26] Clearly, this table is based on potential equilibria effectively reached via the proposed algorithm.

Note finally that for the cases that reach a given equilibrium, the steady state distribution over networks, the prices and values obtained from the MPE calculations are computed with very little dispersion over runs.

TABLE 3.2: Characteristics of MPE over 5,000 runs, selected parameters

Setting	Iter Mean	Iter SD	Equil 1	$P(g_{11} = g_{22} = 1)$	$\overline{t_{11}}$	$\hat{\sigma}_{t_{11}}$	$V^1_{\textit{Equil 1}}$	$\hat{\sigma}_{V^1_{\textit{Equil 1}}}$
1: No heterogeneity - Constructed Multiplicity	11.961	2.092	0.513	0.99999	34.352	0.004	1.328	0.000
2: Moderate Heterogeneity	11.532	2.819	0.585	0.99999	32.795	0.007	1.359	0.000
3: Moderate Heterogeneity and High Costs of Linking	11.898	1.132	0.636	0.99999	48.316	0.005	1.049	0.000
4: Strong Heterogeneity	11.926	2.149	0.966	0.99999	35.904	0.004	1.477	0.000
5: Strong Heterogeneity and High Costs of Linking	12.373	2.619	0.941	0.99999	39.007	0.004	1.415	0.000
6: Strong Heterogeneity and Competing Buyers (A)	12.444	3.004	0.345	0.99999	35.901	0.006	1.477	0.000
7: Strong Heterogeneity and Competing Buyers (B)	11.846	2.065	0.478	0.99999	35.901	0.006	1.477	0.000
8: Strong Heterogeneity and Unequal Bargaining Powers	18.353	2.391	0.873	0.99999	13.540	0.024	1.924	0.001

3.5 Parameters and Market Outcomes

The parameter *sweeping* described in the previous section is useful for illustrating the main predictions of the model. The caveats discussed above around multiplicity challenge the validity of conclusions drawn from comparative exercises based merely on exploring changes in equilibrium outcomes after variations in the fundamental parameters of the game. The references to the equilibrium computations in this section are then illustrative only and serve the purpose of supporting a qualitative description of the mechanics of the game [27].

The game presented here is such that the *architecture* of buyer-seller relations and the prices underlying these are a result of the surplus-sharing rules, the heterogeneity in the matching quality and the existence of linking costs. Below I summarise in seven statements, the main ways in which these three sets of parameters can affect the observed networks and prices, to turn, in the next chapter to the discussion on structural estimation.

[27] For these illustrations, consider the same simple setting of two identical buyers with a unit demand over an indivisible product that can be supplied by two sellers that are constrained to producing for, at most, one or other buyer in each period. The key parameters we are interested in are the bargaining power of the second buyer, b_2, (given that that of the first buyer was fixed at 0.5 for the whole of the *sweeping* exercise), the cost of linking with a new buyer, c_{high}, and the quality of the matches of the second buyer with either seller, ρ_{21} and ρ_{22}. Once more, recall that the there is no cost of breaking a link and that the cost of re-linking with an *old* supplier is fixed for the whole exercise. Similarly, ρ_{11} and ρ_{12} are set so the quality of the match between buyer one and seller one is higher than that between this buyer and seller two.

First, a buyer with no bargaining power (take-it-or-leave it offers from sellers) will not link when costs of forming a link are sufficiently high. This is a straightforward statement. When one buyer has no bargaining power, the probability of observing only the other buyer trading increases with the costs of forming a new link. As in our *sweeping* exercise, fixing the bargaining parameter of buyer 1, $b_1 = 0.5$, note that whenever $b_2 = 0$, buyer 2 doesn't trade, in the presence of non-zero costs of linking. When the costs of forming a new link are the same as those of maintaining a link, buyer 2, even with no bargaining power might still form links and the ergodic distribution over states show networks in which only buyer 1 trades with probability 0.46. As the cost of forming links increases, networks with buyer 1 as the only buyer in the market arise with a steady state probability of above 0.85 (with $\bar{c}$ above a certain threshold, this probability is 0.99). Remember that the no-linking alternative for the buyer was set to a value unappealingly low. Then, under this set up, it can be seen that when the costs of forming a new link are non-zero, if a buyer is trading, then the profit-sharing rule cannot be one in which the seller captures all the surplus in a relation. The bargaining parameters to be estimated with our data, then, need to be consistent with this observation.

Second and related to the previous point, when both buyers have at-least-some bargaining power, networks with one buyer only occur with probability close to zero. The out-of-the-market option for the buyer was set low enough so that trade always dominates the option of not-linking. So long as each buyer can extract at least some of the surplus produced in trade, they will both be active. This can be under networks that are *coordinated*, so that there is no clumping of both buyers choosing the same seller or with *miss-coordination*, happening when both buyers choose the same seller. Note however that buyers' linking choices occur simultaneously so no purposeful coordination is possible. Recall as well that the presence of private shocks prevent buyers from making certain conjectures over rivals' choices. Clumping occurs with significant non-zero probability only when buyer 2 has no bargaining power. Above that, irrespective of the parametrisation of the heterogeneity in the matching quality, both buyers trade and they do so by linking with different sellers. In our exercise, this implies observing a network where the only two links are $g_{11} = 1$ and $g_{22} = 1$ or one in which these are $g_{12} = 1$ and $g_{21} = 1$.

Third, in equilibrium, buyers choose different suppliers. In the game proposed here, sellers are constrained to supplying one unit of the product only. Whenever two buyers link in negotiation with the same seller, one of them (precisely the one that offers lower gains from trade to the seller) will not trade in that period, paying -if any- the associated cost of having linked and obtaining the outside value. This induces the buyer moving away from that particular seller, onto the second best option. The other buyer, who offers the largest gains to the seller, will trade. However, given that larger negotiation sub-graphs for the seller improve her bargaining position, this will drive the price up, making states of clumping less valuable for the remaining buyer, even when she succeeds to trade. This result is important for the structural estimation, as the links we observe in the data will be the result of equilibrium behaviour that does not involve unrealised links (which we, obviously, cannot observe).

Fourth, when faced with more than one potential buyer, the link that prevails with a given seller is the one that maximises the gains from trade for the seller which depends, via negotiated prices, on the relative bargaining powers and the matching qualities. Other things equal[28] buyers with lower bargaining power are preferred and better matches are preferred as well. Note however, that the effect of the quality of the match on the seller's choice is mediated by the bargaining parameter itself and the higher the bargaining power of the buyer, the lower the effect of the quality of the match on the price and, therefore, on the seller's profits.

Fifth, the presence of heterogeneity in the matching qualities induces sorting but not necessarily the most efficient outcome. This is immediately related to the shape of the period profits. As the quality of the matching ρ_{ij} enters additively in the unit profits of the buyer, it is clear that, other things equal, buyers would in principle be inclined to linking with their best match. However, when the best match for both buyers corresponds to the same supplier, in equilibrium, the outcome network corresponds to that which exhibits higher gains from trade from the seller's perspective, with the "discarded" buyer moving away to the second best alternative. This does not always imply that in the presence of matching-level heterogeneity the fully efficient network arises. To see this, consider a case in which $\rho_{21} > \rho_{22} > \rho_{11} > \rho_{12}$ and $\rho_{11} + \rho_{22} > \rho_{21} + \rho_{21}$. In such a setting, both buyers prefer, other things equal, seller one. However, the gains from trade for that seller are higher with buyer 2. This can force buyer 1 to link with his second best alternative, seller 2. Although this outcome maximises seller 1's and buyer 2's profits, it leads to a network that does not produce the industry efficient outcome. The decentralised linking protocol proposed here leads to the prevalence of the network that maximises industry-wide gains from trade, within capacity constraints and in the presence of matching heterogeneity in the ρ ordering of this example, only if $\rho_{11} + \rho_{22} \leq \rho_{21} + \rho_{12}$.

Sixth, higher costs of linking generate stronger persistence in pre-existing links and drive prices up. This as well constitutes a natural result from the structure of the game. The effect of the cost of forming a new link operates in two ways. As it negatively affects the period profits for the buyer, irrespective of the result in the bargaining stage, other things equal, higher linking costs lower the value of opening new links for a buyer. With

[28]Critically, buyers' sizes, retail and input prices.

it, the future value of moving away from the current supplier is also low, making the relative gains from the current relation higher and driving the price up, for a fixed set of bargaining parameters. This can then mimic settings in which the buyer allocates systematically orders to its existing supplier(s).

Seventh, the network structure affects both the prices, via outside options, and the discrete choice decision in a way that is similar to entry / exit problems. In our simple setting, buyers are allowed to choose one link only, linking decisions are non-coordinated and other buyers' choices affect the profitability of a given link directly. This feature resembles the strategic aspect of standard entry / exit games in which firms decide whether to enter a market (start a relationship with a seller) with profits being dependent on whether she finds herself a monopolist in the market after entry (she is the only party negotiating with the seller) or whether she is competing with other firms (she bargains with a seller who is sustaining multiple negotiations at the same time). On top of this *direct* effect, the choices of rivals situated in other areas of the graph play a strategic role as well. To see this, consider a buyer facing two different possible suppliers, s_1 and s_2 and assume that the buyer we are interested in, buyer 1, negotiates and trades with s_1 and another buyer, buyer 2, trades with s_2, under set costs of linking, qualities of the matches and other exogenous primitives. Upon successful trade, each buyer needs to make a new choice of suppliers for the next period. Buyer 2 will be perceived as more likely to re-link with s_2 than any other supplier. From buyer 1's perspective, then, the probability of any state of the world arising with buyer 2 linking with any seller different from s_2 is lower. This affects the continuation value for all the choices buyer 1 could potentially make in the current period and the equilibrium prices associated to these. To continue with the analogy to entry / exit games, the problem presented here could be interpreted as one in which each seller represents a market and each buyer is a firm who needs to decide what market to enter. Each market can hold one monopolist only, whose cost (price to be paid for the garment) depends on (the identity of) other incumbents or entrants both via the competition in the current period and the probability distribution over states that can be reached in the future. A problem that is similar to the one described here is that studied by Aguirregabiria and Ho (2010), who find this network effect as the underlying mechanism supporting entry deterrence. However, for the purpose of their model and its estimation, they propose an independence assumption across markets (sellers in analogy to our setting) that simplifies the game substantially.

Finally, note that up to here we have imposed symmetry in three relevant aspects of the buyers' characteristics: we have assumed that they charge the same price in their domestic markets $r_i = r$, that they place orders of the same size $q_i = q$ and that they require the same quality of inputs $m_i = m$. Other things equal, it can be easily seen that larger buyers will *win* the competition for a seller when many-to-one situations arise. Although higher r_i's will also increase the surplus the seller can extract, this is only via the gains from trade for he buyer in the bargaining process. This implies that, capacity constraints aside and heterogeneity assumed away, a supplier will prefer a large buyer with low end-market prices than a smaller buyer with high prices. The cost of the inputs enter linearly in the sellers profit function as well, having still a greater impact in the stability of a given link than that of r_i.

All of these[29] are observed in the data, together with the active links (who trades with whom) and the prices at which trade takes place. The game proposed here models these two as results of the equilibrium behaviour consistent with values of three (sets of) parameters: the cost of linking, the bargaining powers of the buyers and the shape of the matching-specific heterogeneity component. The following chapter proposes a first exploration to the structural estimation of these using observed matches and prices.

[29] Except for r_i, which I will show it can cancel out in the estimation procedure

Chapter 4

The Structural Approach

4.1 Introduction

The previous chapter described a dynamic game of incomplete information in which buyers choose a supplier for a product, from a list of available sellers in a market. The game gives, as its main outcome, a configuration of a buyer - seller network and a set of contracts associated to it. These were the result of a process of competition between buyers for suppliers of heterogeneous qualities and a sunk cost of starting a relation.

This chapter discusses and assesses the applicability of the econometric approach developed in Lee and Fong (2013) for estimating the structural parameters of the game. In terms of its structure, their estimation algorithm resembles that of Bajari et al. (2007) with two stages performing a forward simulation routine to compute value functions and an iterative procedure that evaluates candidate parameters to compare the results produced by these with conditional choice probabilities recovered non-parametrically from the data, as in Hotz and Miller (1993). There are two aspects in which Lee and Fong's algorithm explicitly differs from that of Bajari, Benkard, and Levin. First, a fixed point problem in prices-to-values is nested in the computation of value functions, looping from computed values to prices and back to values iteratively until convergence to guarantee internal consistency of these two. This is similar to what was done in Chapter 3 when realising an example of a small game and computing its equilibrium(a). Second, the estimation of the structural parameters is done via the minimisation of a distance score that compares conditional choice probabilities that need to be computed for each parameter candidate. In the exercise I perform in this chapter using simulated data, this proves very costly in terms of computer times and the advantages of the method over alternatives that rely on computing fully the equilibrium of the game for each candidate are dubious.

There are a number of specificities of the data and the problem at hand that make Lee and Fong's algorithm not immediately applicable. This has led to the introduction of extensions and alternative steps in the algorithm in three dimensions: (i) the way in which conditional choice probabilities are obtained from the data; (ii) the use of data on prices; (iii) the construction of the score to minimise. The extensions related to (i) and (iii) follow suggestions in Bajari et al. (2007) and Hotz et al. (1994), while those in (ii) respond to the availability of additional information in our data. These extensions lead to sixteen different ways of applying the algorithm to my setting.

After framing the techniques used here in the empirical IO literature, the goal of this chapter is to present the algorithm and its alternatives and discuss the results of applying them to estimating the parameters of the simple game presented in Chapter 3 using simulated data. The main aim of this exercise is to shed light on the suitability of the methods to my setting and in no way constitutes an attempt of evaluating the merits of the econometrics underlying Lee and Fong's algorithm in broader terms. What I present here pursues a different goal and does not display the rigour necessary to propose claims that could exceed the limits of this first exploration.

The next section, 4.2, discusses the econometric approach, with references to the recent literature on the estimation of dynamic games of incomplete information. Then, in 4.3, I present the structure of the chosen estimation algorithm, following the developments in Lee and Fong (2013). Section 4.4, describes the operational assumptions needed to implement the econometric approach to estimate the proposed game using our data. Finally, section 4.5 presents the results from a small Monte Carlo exercise that studies the performance of the algorithm and its variations and discusses the main difficulties encountered when applying it to our setting.

4.2 The Econometric Approach

The game proposed in Chapter 3 constitutes a dynamic game of incomplete information. Lee and Fong (2013) propose a two-step procedure to estimate the parameters in this type of problem when actions are networked in a non-trivial way.

The computational difficulties associated to the estimation of dynamic problems are well understood. Until recently, the origin of these difficulties has been the need for solving the underlying dynamic programming problem: continuation values needed to be generated by finding a fixed point in the value function for each player, repeating this process for different parameter candidates to search for the one that mimicked the observed behaviour best [1]. The burden imposed by this type of procedure naturally increases with the number of players, making the computational problem particularly severe in the context of strategic games. The literature in this area, in the last decade, has then focussed on alleviating the computational costs imposed by the fixed point procedure.

The developments that are more relevant to the work I present here exploit the *Invertibility Result* proved in Hotz and Miller (1993) in the context of a single-agent dynamic discrete choice problem: under relatively general assumptions, it can be shown that there exists a one-to-one mapping between the choice specific value functions and the conditional choice probabilities induced by the dynamic programming problem, in a fashion that is similar to static discrete choice problems. Moreover, the invertibility of that mapping allowed for estimating non-parametrically the continuation values, using the choice probabilities in the data, without computing the fixed point problem described above [2]. Early generalisations of this original idea were presented in Hotz et al. (1994) offering an extension, based of forward simulation techniques, of the findings in Hotz and Miller (1993) to problems with no terminal state. Rust's chapter in the 1994 Handbook offered a survey of these methods under a unifying framework (Rust, 1994).

Different adaptations of these techniques to games with strategic interaction were proposed (see Aguirregabiria and Mira (2007); Bajari et al. (2007); Pakes et al. (2007) as salient, but not exclusive, examples) and the reader is referred to Ackerberg et al. (2007) and Aguirregabiria and Mira (2010) for comprehensive surveys on the literature.

The immediate additional complication associated with moving from single agent to multiple-agent problems is the (potential) multiplicity of equilibria. As pointed out in Pakes et al. (2007), non-uniqueness in games of strategic interaction implies the impossibility of working out the probability distribution over possible outcomes, conditional on the parameters and the set of observable variables. This, in turn makes most standard estimators unsuitable for settings in which multiple equilibria are possible, aggravated when the relevant dimension of heterogeneity across agents grows and, with it, the scope for multiplicity as it tends to be the case in network formation games.

The type of game I propose belong to the class in Ericson and Pakes's general framework for Markov industry dynamics (1995). Their first and second Theorems state the conditions that underlie the "one-MPE-data" assumption, that most of the econometric approaches relevant to my work make. Proposition 1 in Pakes et al. (2007) states that, under certain assumptions, each equilibrium of the game generates a finite chain

[1]These complications are not exclusive to the multiple-agent setting. The single agent problem in Rust (1987) already evidenced this.

[2]This is stated as Proposition 1 in Hotz and Miller (1993).

of actions and states that depend only on their current and immediately observable realisations. This (once more *finite*) chain defines a recurrent class of states that are the only visited states. Then, given a data generating process consistent with a given recurrent class, the policies of the players that correspond to that data generating process need to be the same across all equilibria. In other terms, given the current state, the distribution of future states can be computed and policies are well defined functions of the parameters and observables (Ericson and Pakes, 1995; Pakes et al., 2007).

A number of alternative two-step estimators were developed, making use in one way or another of the "one-MPE-data" assumption and some form of non-parametric circumvention of the explicit computation of continuation values. The general structure of the estimators is similar across all these alternatives. They all share a *first stage* in which transition probabilities over states and players' conditional choice probabilities are obtained from the data. A *second stage* then searches for the parameters that best match the observed behaviour, using the conditions of a Markov Perfect Equilibrium in the corresponding game. This requires no actual computation of en equilibrium.

The first step in this direction was, of course, that taken in Hotz and Miller (1993). The improvements on their framework have largely been devoted to i) introducing more engaged interactions between individual current profits and rivals' actions and ii) reducing the sample bias induced by the fact that continuation values are estimated in a first stage and "fed into" a second stage from which the parameters are recovered with, potentially, sample bias [3].

It is in the tradition of these two-step estimators that I exploit the advances in Lee and Fong (2013) to recover the structural parameters of the game I am interested in. In its most general form, the estimation procedure suggested in Lee and Fong (2013) imposes some additional challenges when implemented in my setting. The first one is that, like in many other applications, the state space is indeed large and exponentially growing with the number of players. Even when all states of the world were visited with equal probability, stepping in each of these at least once would require an unrealistically long panel. Moreover, as it will be seen below, the type of data I work with, shows high recurrence in linking choices, generating observations compatible with a distribution over states that never visits some of its nodes. The second one is that in my setting I do observe the prices of interactions that take place in the data, so the fixed point that recovers prices needs to be internally consistent not only with the computed value functions, but also with the prices in the data. Finally, the computer times are prohibitively long even

[3]The severity of this depends, among other things, on the size (relative to the data) of the state space and the second stage method, especially if the estimating objective function exhibits non linearities over the estimated values, as in the context of likelihood-based techniques. See Pakes et al. (2007) and Aguirregabiria and Mira (2007) for further discussion on this.

when no full equilibria of the game is computed. Actually, the algorithm in Lee and Fong's approach requires computing equilibrium CCPs for deviations of the parameters, which makes the computation almost as taxing as solving for the equilibrium fully.

The following section presents the algorithm as developed by Lee and Fong, with the variations that correspond to my setting.

4.3 The Algorithm

As in Lee and Fong (2013), consider one market only for notational simplicity[4].

The first part of the algorithm below describes the generation of value functions via forward simulation.

I assume that f^{ϵ} is distributed Type I Extreme Value. Following Hotz and Miller (1993), if the probability of player i choosing each action under each state, $P_i(a_i|g)$ (the conditional choice probabilities), can be estimated from the data, differences in the choice specific value functions, $v_i^{\sigma}(a_i, g)$ in equation 3.8 in the previous chapter, can be recovered as:

$$v_i(a,g) - v_i(a',g) = ln(P_i(a|g)) - ln(P_i(a'|g)) \tag{4.1}$$

for any two actions a and a'. Then, the estimated policy function for agent i would be given by:

$$\hat{\sigma_i}(g,\epsilon_i) = argmax_{a\in A_i}\{v_i(a,g)+\epsilon_{a,i}\} = argmax_{a\in A_i}\{ln(P_i(a|g))+\epsilon_{a,i}\} \tag{4.2}$$

For any set of policy functions $\{\sigma_i, \sigma_{-i}\}$ consistent estimates of value functions for agent i and all rivals playing those strategies, can be obtained using:

$$\hat{V}_i(g,\sigma,\theta) = \mathbb{E}\big[\sum_t^{\infty}\beta_i^t(\pi_i(g^t,\mathbf{t}) - c(g^t|g^{t-1}) + \epsilon^t_{i,\sigma_i(g^{t-1},\epsilon_i^t)})|g^0 = g, g^t = O(\tilde{g}(\sigma(g^{t-1},\epsilon^t))),\theta\big] \tag{4.3}$$

[4]Note, however, that for the estimators to have desirable properties, all the states in a certain recurrent class need to be visited infinitely often. In the context of our panel, where a number of markets are observed over time, this would require (for example) assuming that the initial state in each market is a drawn from the ergodic steady state distribution of states.

Expectations are taken over present and future ϵ's, the O rules and $\mathbf{t}$ are consistent with $\hat{V}$, following the Nash bargaining procedure.

Let θ be the vector of parameters. The approximation of these value functions is done iteratively using the forward simulation in Bajari et al. (2007), following the steps below[5]:

1. Fix θ.

2. Set $\mathbf{t}$ and $O(\cdot)$, in the first 'round' of the process to be an initial guess.

3. For each g, iterate to generate $V_i(g; \sigma; \mathbf{t}^k, O^k, \theta)$, where in each iteratiion τ:.

   (a) Set $g_\tau = g$, the network fixed above.

   (b) For each agent i, draw error shocks ϵ_i^τ for each action that can be taken.

   (c) For each agent i, calculate actions $a_i^\tau = \hat{\sigma}_i(g^\tau, \epsilon^{\tau_i})$, as the profit maximising action.

   (d) Using the a_i's for all players obtain the negotiation network $\tilde{g}(a^\tau)$.

   (e) Using $O(\cdot)$, obtain the stable network that arises from the predicted negotiation network, $g' = O(\tilde{g}(a^\tau))$.

   (f) For each i compute the stage profits $\pi_i(g', \mathbf{t}) - c_i(\tilde{g}(a^\tau)|g') + \epsilon^\tau_{a_i,i}$.

   (g) Update the network to be $g^{\tau+1} = g'$ and repeat steps 3.a to 3.g up to T times. This constitutes one path of play.

   (h) Generate multiple paths of plays following the steps above, starting with network g in the first iteration.

   (i) Average each i's discounted stream of payoffs for the multiple simulated paths of play to obtain an estimate of $\hat{V}_i(g; \sigma; \mathbf{t}; O^\tau, \theta)$.

4. Repeat step 3 for all the possible states of the world[6].

5. Update $\mathbf{t}^{k+1}$ and O^{k+1} using the $\hat{V}_i$ estimated for each i and g, solving the bargaining problem.

6. Use $\mathbf{t}^{k+1}$ and O^{k+1} to re-start the process in step 2.

7. Repeat steps 2 to 5 until $\hat{V}_i(g; \sigma; \mathbf{t}^k; O^k, \theta) - \hat{V}_i(g; \sigma; \mathbf{t}^{k-1}; O^{k-1}, \theta) < \omega)$, where ω is a specified cutoff.

[5] Although the algorithm is presented differently the main structure corresponds to that in Lee and Fong (2013).

[6] Note this is different from Lee and Fong (2013).

The steps above, in our context can be modified to allow for the observation of prices. Step 5 computes prices in the Nash Bargaining problem for all the linked pairs under all possible states of the world, given θ. However, for the networks that are present in the data, prices can be directly observed and excluded from this step, restricting the computation of prices to the counterfactual instances (in disagreement points) and to unobserved states. This leads to two alternatives that will be explored in the following section.

The following part of the algorithm estimates policy functions and finds the parameters that minimise deviations from observed data.

1. Obtain equilibrium CCPs, $\hat{\sigma}_i(g)$, non-parametrically from the data.
2. For each i, compute the optimal policy $\tilde{\sigma}_i(\cdot;\theta)$ given that all other players are playing $\hat{\sigma}_{-i}$ following:
   (a) Start with candidate policy $\tilde{\sigma}_i^{\tau} = \hat{\sigma}_i$.
   (b) For iteration τ let $\overline{\sigma}^{\tau} = \{\tilde{\sigma}_i^{\tau}, \hat{\sigma}_{-i}\}$.
   (c) For the probabilities implied in $\overline{\sigma}^{\tau}$ obtain simulated value functions $\hat{V}_i(g;\overline{\sigma};\theta)$ by running the forward simulation described above.
   (d) Update conditional choice value functions $v_i^{\sigma}(\cdot)$ for all actions and states given $\hat{V}_i(g;\tilde{\sigma};\theta)$ and prices obtained after the forwards simulation.
   (e) Update the CCPs for player i, obtain $\tilde{\sigma}^{\tau+1}$ by: $P_i^{\sigma} = exp(v_i^{\sigma}(a_i|g))/(\sum_{a\in A_i} exp(v_i^{\sigma}(a|g)))$.
   (f) Repeat steps $2.a$ to $2.e$ until the P_i^{σ} for all i and in all states under the optimal policy converge, up to a pre-specified threshold. Store the optimal policy of player i given that all other players are playing $\hat{\sigma}_{-i}$ as $\tilde{\sigma}_i(\cdot;\theta)$. As a result, there is one of these per agent.
3. Obtain an estimate of θ by minimising the sum of squared deviations in the choice probabilities induced by $\tilde{\sigma}_i(\cdot;\theta)$ against the policy $\hat{\sigma}_i$ obtained from the data:

$$\hat{\theta} = argmin_{\theta} \sum_{g} \sum_{i} \sum_{a\in A_i} \left(P_i^{\{\tilde{\sigma}_i,\hat{\sigma}_{-i}\}}(a|g) - P_i^{\hat{\sigma}}(a|g)\right)^2 \tag{4.4}$$

The general algorithm above involves at least two aspects in which data limitations can induce bias.

The first one is the non parametric estimation of conditional choice probabilities from the data, for all players and actions and under each possible state of the world. In the context of my problem, the state space is large even for a very small set of players. As established already in the stylised facts in Chapter 2 persistency in choice is high, implying that even in long panels, the probability of observing actions being taken in every state of the world are relatively low. The alternatives that I explore in the next section will involve (i) working with the 'true' CCPs, an advantage I have with simulated data, (ii) estimating the CCPs non-parametrical with a frequencies estimator and using kernel smoothing to estimate the CCPs in unobserved states, (iii) making the parametric assumption that unobserved states exhibit CCPs that correspond to the unconditional choice probabilities over all the observed states, for each player; (iv) making the parametric assumption that all actions in unobserved states can be played with equal probability.

Second, the minimum-distance score that is used for recovering the parameters compares element-wise and adds over every player, action and state. As suggested in Bajari et al. (2007) an alternative to explore could be to sum over the observed states only, at a risk of bias that depends on the application.

4.4 Data Restrictions and Operational Assumptions

Our data constitutes a collection of $m = 1 \ldots M$ markets, observed over time, each with primitives B^m, S^m, $\mathbf{G}^m$ and π^m (estimated). Besides the formal assumptions introduced in Chapter 3, namely, Assumption AS and Assumption CI in Rust (1994) and the parametric construction for ϵ, there are a number of additional operational assumptions that help match our problem better, restrict the size of the game and circumvent data restrictions.

Assumption 1: One Main Order. For narrowly defined markets (see below for a definition), at each point in time, the decision of the buyer can be simplified to that of how to allocate her main or largest order. In a market-quarter realization, each large buyer has a median of 1 supplier, a mean of 1.5 and the 95^{th} percentile is 4. Table C.43 shows that for the bulk of the data the largest order accounts for more than 90% of the buyer's demand. Therefore, the network decision of the buyer in each quarter will involve to choose one supplier to produce the main order in that market and I will consider this a choice independent of that of simultaneous allocations of smaller orders, which I will not include in the analysis.

Assumption 2: No Across-markets Interactions. As shown in the descriptives presented in Chapter 2 each large buyer participates in a high number of product categories simultaneously. The formulation here assumes that the linking decision the buyer makes in a given category is not related to those made in other product categories. This is supported by the evidence I presented in the binary regressions in Table **??** of Chapter 2. Although this restriction needs further empirical scrutiny, it is clear that allowing for sophisticated inter-market considerations can very easily expand the size of the state space and choice sets making the problem untractable.

Assumption 3: Constant revenues in the retail market for each buyer. Our data does not contain information on the retail markets. The formulation of the profit function of the buyers and that of the Nash bargaining problem assumed that in their retail markets, the price and quantities that the buyer sells are the same, irrespective of the seller producing the garment. This is compatible with a setting in which (i) there are no demand-relevant differences in the garment produced by different manufacturers and (ii) retailers decide end prices ex-ante. While the first assumption doesn't seem too far-fetched, the second one seems to involve a higher compromise. However, anecdotal evidence collected in interviews with large buyers support this idea and we were explained that when the same product is sourced from different suppliers over time, the price remains unchanged, especially for lines of products that are highly commoditized (basic and seasonal products in Appendix F).

Assumption 4: Constant demand from each buyer. The game I proposed also relies on the idea that players do not anticipate growth in the size of the order. This means that when computing the future value of each relation and then, the values over states, players assume that future orders of a buyer have the same size as her current orders. This could be modified introducing expectations over potentially buyer-specific growth paths. This is an extension that has been evaluated.

Assumption 5: Buyers 'search' in a restricted neighbourhood within the product category. Alternative definitions of a *market* are possible and so far I have used markets and products as synonyms. However, when markets are defined as product categories (HS code at six digits of disaggregation), choice sets can be prohibitively large for the structural procedure. Even imposing additional restrictions, like those in the reduced form regressions of Section **??**, the state space can grow too large if we allow the buyer to contemplate a high number of potential suppliers[7]. The exercises performed in Chapter 2 and presented in table **??** showed that the predicted probabilities of a seller being allocated an order (of a given product -HS6- at a certain point in time) was, other things equal, 'small' when the standard of the seller, measured in deciles in the distribution of prices, was far from that in which the order finally fell. The intuition behind this is that a product category (for example, Men's shirts made of cotton) is still a very broad category. Assuming that any manufacturer can supply garment to buyers as dissimilar as Tommy Hilfigher and Primark seems unsuitable. The operational assumption I propose, then, is to divide each product category in deciles of its distribution of prices. Then, a market in a given point in time is a combination of a product and a decile[8]. Using this definition, implies assuming that a buyer's "search" for a supplier happens in a small neighbourhood within the product category, where the neighbourhood is determined by the price of the order. Because prices are an outcome in the model, this assumption will need to undergo further testing in the structural estimation stage.

Assumption 6: One Equilibrium in all Markets. One of the highest requirements of this econometric approach, like in similar two-step estimators, is that of the 'uniqueness' assumption it implicitly imposes on the data. Estimates of the policy functions and transition probabilities require the availability of rich enough data on actions and states, generated from the same equilibria. This can prove quite demanding on many empirical settings, leading to the implementation of different generalising assumptions in the equilibrium selection protocol in applied work. A vast number of papers tends to pool data across markets under the assumption that the same equilibrium is being played in all the markets (Aguirregabiria and Mira, 2007; Collard-Wexler, 2013; Ryan, 2012; Suzuki, 2013). If the underlying data generating process violates this assumption, then the estimated policies will be a combination of those under the true equilibria and inference is not possible. Recent research has explored ways of testing for the unique-equilibrium-across-markets hypothesis (notably, Otsu et al. (2014)) and future research could implement these.

4.5 Results from a Preliminary Monte Carlo Exercise

Following the discussion in the Section 4.3, here I present an exercise that recovers the parameters of a game from which data is simulated, visiting the alternatives for the

[7] Table 3.1 showed the exponential growth with the number of sellers in computer times required per iteration in the MPE computation. Even when equilibria is not computed, the number of points the forward simulation needs to visit can get prohibitively large.

[8] This definition gives 480+ markets in our data.

estimation introduced in the previous section. These are:

1. On the estimation of CCPs:
   (a) Using the 'true' underlying probabilities computed as the equilibrium of the game.
   (b) Using a frequencies estimator with a kernel for unobserved states.
   (c) Parametric assumption 1: unobserved states exhibit CCPs that correspond to the unconditional choice probabilities over all the observed states, for each player.
   (d) Parametric assumption 2: all actions in unobserved states can be played with equal probability.
2. On the computation of prices:
   (a) Treat all prices as unobserved.
   (b) Exploit observed prices.
3. On the distance score:
   (a) Summing over all possible states of the world.
   (b) Summing over observed states only.

The combination of these alternatives gives 16 possible estimations, which are performed over simulated data for a 2×2 setting. For this exercise I simulate data coming from the MPE computed using the algorithm presented in Chapter 3 when the true bargaining parameters and cost of linking are $c_{high} = 12$ and $b_1 = b_2 = 0.5$ and these are the parameters to be estimated. Heterogeneity is fixed and left outside of the estimation with $\rho_{11} > \rho_{12}$ and $\rho_{22} > \rho_{21}$ with $\rho_{21} = \rho_{12}$ and $\rho_{11} < \rho_{22}$. The computation of the MPE produces, reasonably, strategies under which buyer 1 always (under every state of the world) chooses seller 1 and buyer 2 always chooses seller 2. This gives simulated data as 'extreme' as it can be, in the sense that only one choice per player is observed and only one state is visited. Although this might seem unrealistic, the ratio of observed to unobserved states (1/8) is similar to that of what we can observe in actual (non-simulated) data for networks of realistic dimensions.

Before discussing the results of the comparative exercise, a comment on computation costs is in order. The algorithm as proposed by Lee and Fong (2013) and 'augmented' with alternatives here, does not necessarily *economize* on computing time, relative to methods that compute the full equilibrium of the game for each candidate parameter.

The standard linearity simplification that papers using BBL or BBL-inspired techniques cannot be exploited in this setting (Bajari et al., 2007).

To reduce computer times, the minimisations in the estimation routines for all exercises except from that of the true probabilities, were run on a constrained set, setting a scanning grid around the true value of the parameters. The unconstrained exercise is necessary for a full assessment of the methods presented here and is being performed at the time of this submission.

True Probabilities in CCPs. When the 'true' underlying probabilities are used as estimated CCPs, which we can do in this simulated exercise, the performance of the estimators in terms of biases depends on the use of the prices. When the observed prices are fed into the generation of the value functions (so only the unobserved prices need to be generated), the parameters are recovered exactly (up to the 4th decimal, at least) irrespective of whether the minimisation is done over a the score considering every state or only observed states. Instead, when the prices are treated all as unobserved, the empirical mean of the estimates shows a significant bias, with $\hat{c}_{high} = 4.9$, $\hat{b}_1 = 0.63$ and $\hat{b}_2 = 0.68$.

Frequency Estimator with Kernel. When the CCPs are estimated using a frequency estimator for the observed states and a discrete kernel approximation for the unobserved ones, the results of the estimation routine are strongly biased and, again, coincide across the two alternatives of objective function. When all prices are treated as unknown, the empirical means are $\hat{c}_{high} = 12.05$, $\hat{b}_1 = 0.68$ and $\hat{b}_2 = 0.88$. When, instead the observed prices are used, $\hat{c}_{high} = 12.17$, $\hat{b}_1 = 0.61$ and $\hat{b}_2 = 0.72$. All the estimates are severely biased upwards. Given that these estimations were constrained to scan around the true values of the parameters, no comparison of the $\hat{c}_{high} = 4.9$ obtained when true probabilities were used and the $\hat{c}_{high}$ here is actually conducive.

Frequency Estimator with Unconditional Assumption. When the unobserved CCPs are imputed the value of the unconditional probability of each action being chosen by the player, the results show a smaller but still significant bias. Once more, there are no significant differences over alternative specifications of the objective function. When all prices are treated as unknown, the empirical means are $\hat{c}_{high} = 11.59$, $\hat{b}_1 = 0.62$ and $\hat{b}_2 = 0.78$. When, instead the observed prices are used, $\hat{c}_{high} = 11.05$, $\hat{b}_1 = 0.49$ and $\hat{b}_2 = 0.43$. The sign of the bias in this case depends and, although c_{high} is underestimated, the bargaining parameters are closer to their true values in the specification with observed prices than in any alternative procedure proposed here.

Like in similar two-step approaches, having the value functions estimated rather than computed induces sampling errors. In our setting, this seems to be - as expected - significantly aggravated by the size of the state space and the proportion of it that is never observed in the data. Further alternatives to mitigate this small-sample bias problem need to be explored.

The example used here is, as explained above, as 'extreme' as it can be and the problems in the estimation of the CCPs is as bad as it can be: agents are only observed under one state of the world and they are always observed taking the same action. The underlying parameters are such that the unconditional choice probabilities reflect the probabilities in every state as well, possibly explaining the 'better' performance of the estimators with the unconditional assumption imposed on unobserved states, as opposite to the Kernel and the equal-probabilities assumption.

This characteristic of the MPE and simulated data is likely to be the main driver of the lack of differences between the minimisations ran over the score including all the states and that only restricting to the ones that are observed. This is an avenue to be explored further in order to simplify the computation procedure.

In addition, the almost-exact recovery of the parameters when true prices and true probabilities are used is encouraging as well and implies that there is a potential gain in exploiting this information available in our data.

The exercises presented here are rather limited and constitute just a first exploration of the performance of the two step estimator in our context. The main goal of this study was to evaluate potential paths of improvement of the econometric approach to fit our setting. Conclusions on this and a (necessary) more extensive and rigourous computation are in order.

Chapter 5

Conclusions

The research presented here, as introduced in Chapter 1, aimed at contributing towards understanding how manufacturers' heterogeneity affects the configuration of trading relations and prices in a dynamic environment. The advances in that direction were four: (i) the construction of a dataset containing detailed information on interactions between manufacturers in a developing country and buyers in the rest of the world; (ii) a reduced form characterisation of the interactions between heterogeneity and two market outcomes: the 'persistency' in the choice of supplier and the price-cost margin in the supplied orders; (iii) the construction of a game of buyer - seller linking with bargaining, that realises the observed relations; (iv) a first evaluation of structural techniques to estimate such game with our data.

As shown in the Appendix, our dataset allowed a characterisation of buyer - seller relations in trading markets unprecedented in the literature. The empirical facts collected here suggest that relations are highly persistent, almost exclusive within the product category and growing over time, conditional on survival. In particular, the probability of survival after a first year of relationship is positively related with the intensity of trade (volume and number of products) and prices. Controlling for volumes, input prices and product-specific effects, manufacturers that are paid higher prices tend to survive beyond the first year of relation more frequently. Beyond the first year of relation, survival of the relation seems to be related to the *continuity* or frequency (in terms of the number of *seasons*) of trade in buyer-seller pair. In addition, supporting a picture of exclusive dealing, engaging in trade with a second large buyer increases the probability of breaking up a relation with the incumbent large buyer within the first year of trade. Likewise, for established relations, the hazard rate of stopping trade increases significantly when the supplier starts a new relation with another large buyer. Finally, traded volumes in established relations tend to grow over time, driven by the allocation of a higher number of orders to the seller, rather than by increasing the volume of the orders. In addition, the margin between input and output prices at the order level also grows with subsequent orders and it is highly persistent over time.

The goal in 2 was to explore the relation between the heterogeneity across suppliers and two market outcomes, closely linked to micro-level decisions common to most trade matching settings: who trades with whom and what prices are paid for the items sold. Exploring this relation required capturing a measure of seller-level heterogeneity. The existing literature pursuing comparable endeavours has either gone down the route of fully parametric estimations of production functions or has identified an observable characteristic - typically, size - to capture such heterogeneity. In various settings, the latter has proved to be questionable: in markets where quality and product differentiation plays a significant role, volumes are not necessarily a good proxy for the success of the seller. Similar arguments have been raised against the use of prices for such purposes. Instead, the approach presented here exploited the high level of disaggregation of our data to extract sellers' types as a fixed effect in a volumes-to-prices equation. The high dimensional two-way fixed effects problem here, mimicked exercises that the literature on Labour Economics has performed for decades. This approach was fully discussed in the Appendix.

A first characterisation of the distribution of seller's types showed that the dispersion in these types was higher in those product categories that are typically more fashion sensitive. As expected also, the distribution of types of suppliers trading with large experienced buyers constituted a shift upwards of the one corresponding to non-large buyers.

I then constructed a measure of the heterogeneity across sellers an individual buyer is facing when allocating an order. This required assuming what the set of available sellers to that buyer would be, for the choice under evaluation. In the main text I used a general approach considering all available suppliers in the relevant product category. In the Appendix, I included a robustness check involving a more sophisticated construction of such choice sets. Under both approaches, I confirmed the hypothesized result: the *better* the suppliers the buyer is trading with, the less likely it is to switch to unknown suppliers. Moreover, the higher the dispersion of types in the outside option - this is, in the set of unknown but available suppliers - the less likely the buyer is to move away from his known manufacturers.

The second market outcome of interest was the price - cost margin in allocated orders. Under different specifications, we found that, other things equal, when the buyer is allocating an order to a supplier and the heterogeneity across outside options (alternative suppliers) is high, the price - cost margin is also higher meaning. This evidence of a 'premium' for heterogeneity in markups is compatible with bargaining protocols in which prices derive from any form of surplus splitting between trading parties.

The theoretical chapter presented here exploits the characterisation in 2 to construct a game theoretic model where decision makers choose optimally who to trade with and bargain over prices. In simple terms, the game 'starts' with all buyers simultaneously choosing one supplier from a list of available manufacturers by comparing partner-specific inter-temporal profits. The profits derived under each possible choice depend on the cost of forming links, a match-specific component, the future realisations of the network and the prices that the buyer would pay under each configuration of the network. These prices depend non-trivially on the choices of other buyers: the seller's outside option is determined by the offers it can obtain from other buyers that have chosen it as potential supplier. The seller, capacity constrained, will only be able to produce for one of the buyers at most.

The interaction between (i) heterogeneity at the matching level, (ii) sunk costs of forming a link and (iii) competition between buyers determine the *architecture* of the network of trade and its prices. The more formal aspects of the game built directly on the work by Lee and Fong (2013) and are therefore related to Ericson and Pakes's framework to study industry dynamics (1995). Among the various papers that propose dynamic oligopoly models, the specifics of my setting make the game similar to those in structural papers that need to *nest* the computation of the stage profits inside of the dynamic programming problem defined by the corresponding value functions (Benkard, 2004; Markovich and Moenius, 2008). In particular, analysing industry dynamics in the light of *networked* strategic interactions, my framework is related to the work by Aguirregabiria and Ho on the US airline industry (2010; 2012).

In Chapter 3 I implemented for the first time Lee and Fong's algorithm to compute Markov Perfect Equilibria of the proposed game, repeatedly over a fine grid of parameters. This opened a discussion on issues around convergence, computation costs and multiplicity. The final remarks in this chapter emphasised the mechanisms that induce the empirical observations in the institutional environment under study

The game theoretic model presented in Chapter 3 offered the structure needed for 'recovering' the parameters that characterise the salient facts documented in Chapter 2 on inter-firm relations in the RMG sector in Bangladesh. The three sets of parameters of interest in our setting were a scalar containing the sunk cost of linking, a vector of bargaining parameters (one entry for each buyer) and a matrix containing a match-specific quality (one entry per potential pair). Chapter 4, in this preliminary version of my structural work, treats the matching-qualities as observed and reduces the parameter set to the cost of linking and the bargaining powers. This restriction simplified the analysis in this chapter and is left to be relaxed at a later stage, when a more systematic discussion on identification is presented and the challenges described below are sorted.

This final chapter, therefore, studied the two-step procedure proposed in Lee and Fong (2013), building on the work by Bajari et al. (2007), to recover the parameters that realise the equilibrium observed in our data, expressed in active trade and observed prices. I presented a number of operational assumptions required for estimating the game in Chapter 3 using our data. I discussed three aspects in which my setting imposes challenges to the applicability of the structural approach developed by Lee and Fong. The first of these is the availability of prices in our data. Second, the difficulties in the non-parametric estimation of conditional choice probabilities from the data when the state space is large and choices are highly persistent. Third, and related to the previous point, the construction of the distance score adding over states that have no instances observed in the data. This discussion led to a pseudo Monte Carlo exercise that compared (sixteen) alternative estimation procedures.

The overall estimation procedure was based on forward simulation as in Bajari et al. (2007) to obtain value functions. Following Lee and Fong, a prices-to-values fixed point routine was performed to generate prices consistent with those values. I explored the possibilities of (i) generating all prices in the system and (ii) excluding from the fixed-point routine the prices observed in the data, that would then act as 'constraints' in the iterative procedure that solves the simultaneous Nash problems. The second stage of the estimation finds the optimal policies for each player and computes the conditional choice probabilities that would arise under alternative candidate parameters in the equilibrium play. These probabilities are compared with those estimated directly from the data. I explored different alternatives for this step, using the 'true' underlying probabilities in the simulated data as a baseline. These alternatives were: (i) using a standard non-parametric frequency estimator with a kernel to approximate probabilities in the unobserved bins of the conditional transitions, (ii) assuming that the choice probabilities in unobserved states coincide with the observed unconditional probabilities and (iii) attaching equal probability to all actions being chosen by the players in unobserved states. Finally, I looked at constructing the distance score (which in this setting is the objective function in the minimisation problem that searches for the estimates of the parameters) using all the states of the world and only adding up over observed states.

Such exercise showed some evidence implying that restricting the objective function to the observed states, using an auxiliary parametric assumption on the conditional choice probabilities in unobserved states and exploiting the data on prices could be fertile paths to explore towards constructing a more suitable econometric approach.

There are two specific paths this research is following, at the time of this submission.

The first one involves exploring further, in reduced form, some of the topics that were briefly covered in Chapter 2. In particular, measuring unobserved heterogeneity with our data constitutes a topic on its own. As mentioned in the corresponding chapter, the approach implemented here has a number of limitations, connected to the interpretation of the fixed effects recovered from the price equations and the identification of those in the presence of low connectivity. Similarly, the dataset available to us offers a number of alternative channels to test empirically the preliminary hypothesis of competition between buyers, and this is a path to be pursued in the short run.

The second one is connected to the structural aspect of this research. The analysis of the structural framework proposed in Chapter 3 and its associated set of econometric methods in Chapter 4 reveal a number of issues that need to be addressed in order to structurally estimate the model. I consider three to be of immediate relevance.

First, even in simplified versions of the game, the computational burden, both for equilibria and for simulation of values, can be prohibitively taxing. Taking a recent suggestion[1], at the time of this submission two simplifications in the pricing stage are being explored. They imply different sets of assumptions that would show that simpler versions of the gains from trade are sufficient statistics for the computation (or simulation) of value functions.

Second, Chapter 4 assumed matching heterogeneity was known both to players and the econometrician, to facilitate the assessment of alternative estimation approaches. However, both of these are unrealistic. While introducing unobservability for the players in that component of the game can be a very challenging task, I am currently studying identification considerations for (i) recovering the match-specific qualities exactly when these are known by the players but unobserved for the econometrician and interactions take place in a high number of markets; and (ii) recovering only key parameters of the distribution of the match-specific qualities.

Third, the exploration in Chapter 4 suggest that further study is needed on the implications of data limitations. In particular, the size of the theoretical state space and that of the set of observed states proved a relevant source of potential bias in the estimation procedure. Like in most of the papers exposed to this same problem, the solution that is being evaluated involves performing comparison tests with alternative estimates, ex-post. The operational results obtained in the Monte Carlo stage show that restricting the objective function to the observed states, using an auxiliary parametric assumption on the conditional choice probabilities in unobserved states and exploiting the data on

[1] By Victor Aguirregabiria

prices could be fertile paths to explore towards constructing a more suitable econometric approach. Naturally, the validity of these ideas needs to be rigourously studied in a settings in which the Markov Perfect Equilibrium takes different shapes.

Appendix A

Sources of Data

A.1 The Main Source of the Data and its Structure

The main dataset used for this project was constructed collecting the records in Bills of Entry and Exit used for exporting and importing via the main Custom Stations in Bangladesh. The data comprises the information in the main forms in the Asycuda System, as electronically documented by each Custom Office. The National Board of Revenue in Bangladesh, under the corresponding confidentiality agreements, shared records for the period 2003-2012.

As described in further appendices, the most prominent features of this data are that (i) we observe the identity of all the parties involved in each transaction: buyers of Bangladeshi products in the rest of the world, manufacturers in Bangladesh exporting to the rest of the world and buyers in Bangladesh purchasing goods from the rest of the world; (ii) the data is very disaggregated and cross-sectional units are defined by specific items (products classified using Harmonized Codes) within a transaction taking place on a date (dd/mm/yyyy) between a given buyer and a given seller; (iii) moreover, with the caveats to be discussed in the following appendices, we can trace back the imported inputs needed to produce for a given export consignment.

Although our dataset contains the universe of the trade records in all the product categories in the period under study, in what follows we focus only on the garment sector, defined for the rest of the project as the collection of all the product categories within knitted garment (Harmonized Code 61) and woven garment (Harmonized Code 62).

With this as the main source of data, we constructed two major datasets, one for each type of trade flow - Exports and Imports -, performing the cleaning, arranging and robustness checking procedures described in the appendices to follow.

A.2 Additional Sources of Data

For various steps in the construction of the main datasets and to carry out some of the analysis presented in the body of the text, data from other sources was used, as detailed below.

A.2.1 UN Comtrade Data

This contains import and export flows in Bangladesh as compiled in the United Nations Commodity Trade Statistics Database (UN Comtrade). Records were mainly used to cross-check values and quantities (weights) with our main data, up to the sixth digit of disaggregation of the Harmonised Codes.

This source of data was also used to analyse the evolution of demand for imported garment in the main destinations of Bangladeshi exports.

The use of the Comtrade data in this project complies with the Policy on Use and Re-dissemination of UN Comtrade data, and will be cited as "DESA/UNSD, United Nations Comtrade database".

A.2.2 Board of Exporters

The Board of Exporters has *.doc* lists of all the registered exporters divided in broad product categories. For each exporter, they record the name of the plant or firm, an address and the number of employees and machines at the time of registration with the Board. This data was digitalised (almost) manually and was used for cross-checking the identification of ownership structures and locations of firms for over the approximately 7,500 records of firms in garment categories. Unfortunately, the data on employment and machinery was considered of low quality standards and was not used in this project.

A.2.3 BOND Licenses

Two datasets were constructed containing information on BOND licences. The first one comprises the Bonded Warehouses Codes Lists, documenting the warehouse code and the firm name and address. The second one contains the BOND Licence Number and status, the name of the unit or firm, its address, the Business Identification Number (BIN) and other firm-level identifiers. Both datasets were used in the process of cleaning the variable that allows for matching inputs and outputs at the order level, as described in D.

A.2.4 Euromonitor Data

The data on Euromonitor's Dashboard and Supporting Tables for the Apparel and Clothing Sectors in Europe, Canada and the United States were used: (i) to explore the shares of the *large buyers* of garments in their own domestic markets and (ii) to unify buyers' identifiers whenever the name of the Global Brand Owner differed from the National Brand Owner or the Global or Local Brand Name, as any of these could be used interchangeably in the Customs records.

A.2.5 World Bank Survey

For descriptive purposes only, we have accessed the anonymized panel for the 2007 and 2011 waves of the World Bank's Enterprise Survey in Bangladesh restricting our analysis to the firms whose main product was in any of the garment categories. These explorations were used to support or contrast other evidence we have gathered and was treated an anecdotal material, as representability and anonymization limited any further exploitation of this source of data.

A.2.6 Series of Prices of Cotton

Monthly time series of the price of raw cotton were obtained from the United States National Cotton Council's Economics Data Center. For the period of our data, we have both the so called "A" Index and the spot price. While the first one is a proxy for the world price of cotton, averaging the cheapest five quotations from a selection of the principal upland cottons traded internationally (CFR Far Eastern main ports terms or CIF Europe values), the second one represents cash sales of cotton, with prices reported by the Market News Branch of USDA's Agricultural Marketing Service. For our calculations, except when otherwise stated, we use the proxy for the international price.

A.2.7 Exchange Rates

These were obtained directly from the Custom Offices with daily frequencies for the conversion of the currency of invoice to local currency. Unless specified, values in the documents associated to this project are in US dollars.

A.2.8 Members List - Bangladesh Garment Manufacturers and Exporters Association (BGMEA)

The Association is the competent authority for processing the necessary applications for export / import permissions and tax reliefs, so they maintain accurate records of the identities of the exporters, including ownership data in some cases. All woven exporters outside export processing zones need to register with BGMEA, while knitwear-only manufacturers and EPZ firms have alternative associations they can be affiliated to. We obtained the list of Regular and Associated Members in BGMEA, containing the names, addresses, contact details and parent company (in some cases) of all the firms within BGMEA. This was used to in the identification of manufacturers and in the process of cleaning BGMEA identifiers for the purpose of matching inputs to outputs.

A.2.9 VAT Data

This was provided by the National Board of Revenue and contains the Business Identification Number (BIN) of all the firms operating in the garment sector until 2010 (7,033 records), with their business denomination, address and contact details. This data was used for merging with the Customs records via BIN.

A.2.10 BIN codes for Exporters

This constitutes Bangladesh Customs' list of new and old Business Identification Numbers (BINs) of importers or exporters in all sectors, for those firms that have changed their code from the 10-digit system to the 11-digit system. This dataset comprises more than 145,000 records and contains the old and new identifiers, name and address of the firm. This was used for cross-checking the identification of firms using the VAT data and to detect changes in identities due to changes in the BIN registration system.

A.2.11 World Trade Organisation Tariff Download Facility

Most Favoured Nation (MFN) and non-MFN tariffs for garment and garment relevant sixth digit codes were obtained from the WTO records to follow, year by year (2005 - 2012), the tariffs imposed to imports of relevant inputs for garment production into Bangladesh and for imports of knitted and woven garment into United States and Europe.

A.2.12 ESCAP World Bank: International Trade Cost

Used to analyse the evolution over 2005 - 2012 of international trade costs in manufacturing, for flows from Bangladesh to United States and relevant European countries and into Bangladesh from relevant countries supplying fabric and other inputs.

A.2.13 Exporter Dynamics Database, World Bank

Used for producing comparisons of entry and exit dynamics over 2005 - 2012 in relevant garment product categories, for Bangladesh and 4 selected international competitors.

A.2.14 Firm Level Data, Factories Under Accord

Firm-level variables including number of workers and characteristics of the infrastructure in selected plants were obtained from Accord, an agreement between RMG buyers to monitor safety issues in their supplying plants.

Appendix B

Quality of the Main Data and Coverage

B.1 Coverage and Quality of Data

B.1.1 Exports Data

This dataset contains all the records that correspond to exports. A line in this dataset can be read as an item (product as classified using the Harmonized Codes to the 6th digit) within a shipment from a seller in Bangladesh to a buyer elsewhere on a given date. As many shipments are multi-product, the dataset is more disaggregated than the level of the transaction.

Together with other relevant information, the most salient variables in this data contain identifiers for the buyer and the seller (see the corresponding section for our work on *cleaning* the identities of the players), a classification and description for the product, the statistical value of the product, its net mass in kilograms and characteristics of the shipment (mode of transport, terms of delivery, ports, countries, currency of invoice, exchange rate conversions, etc.).

The National Board of Revenue compiled the records coming from the different Custom Stations. The data before 2005 was considered of low quality, as comparisons with UN Comtrade sources and reports from BGMEA showed poor coverage of the universe of trade, both on the exports and imports side. This coincides with the migration into the Asycuda system in the main Custom Stations. Discarding the records before 2005 and restricting the attention to the garment sector only, including both woven and knitwear products, the Exports Dataset contains $3,059,844$ observations. The distribution of these over years and custom offices look as follows:

Table B.1: Frequencies of Observations over Years, Exports Data

Year	Freq.	Percent	Cum.
2005	250,749	8.19	8.19
2006	321,318	10.5	18.7
2007	319,456	10.44	29.14
2008	388,744	12.7	41.84
2009	352,715	11.53	53.37
2010	507,459	16.58	69.95
2011	486,569	15.9	85.85
2012	432,834	14.15	100
Total	3,059,844	100	

Source: Own Calculations.

Table B.2: Frequencies of Observations over Custom Stations, Exports Data

Station	Code	Freq.	Percent	Cum.
Dhaka	101	288,470	9.43	9.43
Dhaka-K	102	25,724	0.84	10.27
Chittagong House	301	510,978	16.7	26.97
Chittagong - EPZ	303	320,340	10.47	37.44
Chottagong Main	305	1,912,337	62.5	99.93
Benapole	601	1,995	0.07	100
	Total	3,059,844	100	

Source: Own Calculations.

These correspond to five Customs Stations in Bangladesh: Dhaka Custom House (101) and Dhaka Export Processing Zone (101/1073), Dhaka Kamalapur (102), Chittagong Custom House (301), Chittagong Export Processing Zone (303), Main Chittagong (305), Benapole (601, land).[1]

As the table above shows, the non-EPZ Stations in Chittagong concentrate the vast majority of the observations. Unfortunately, the *raw* data we obtained from Offices other than Chittagong exhibited some limitations. In particular: (i) there is no data from Custom Offices 101 and 102 available for year 2009 or after September 2010; (ii) the information sent from Benepole only covers years 2011 and 2012; (iii) the identities of the exporters was missing for a large proportion of the observations across al Custom Offices, for years 2011 and 2012.

Using aggregated data, we verified that in any given year between 2005 and 2011, the selected Custom Stations process more than 94% of the total exports (in volumes and in

[1]Note that 301 records as 305 from 2007 onwards.

values) in garments from the country. Of these customs offices, between 2005 and 2011 the non-EPZ Chittagong (305 / 301) accounts for an average of 90% of the exports we observe. After September 2010, due to a change in the system used to record import and export bills, we only have records collected in Chittagong, the main custom station. Still, for the period September 2010 to September 2012, our data accounts for more than 87% of the exported values in garment in Bangladesh.

Using the years in which data from both Dhaka and Chittagong is available, we corroborated that at the firm level, manufacturers tend to use one or other (set of) Custom Station. For this restricted sample, the proportion of transactions that the firm operates via Chittagong is above 91% already in the 25^{th} percentile and it is zero (meaning all the exports circulate via Dhaka offices) in the 10^{th}. The intermediate percentiles mostly exhibit proportions between 80% and 90%. This implies that each Custom Office seems to be self-consisted when transactions are aggregated at the seller level. Equivalent conclusions were reached when aggregating at the buyer level and at the buyer-seller level. These exercises were performed by quarter, by year and over the whole of the panel, excluding the years for which data from any one of the stations was missing.

Benapole is indeed a very small station, dealing with trade transported via land, which is a negligible choice of mode of transport for the bulk of the trade in the sector we are considering.

Finally, the missing identities in the later data will be partially solved when checking the identifiers for the exporters as described below. However, in most of the analysis carried out in this project, the problematic observations were excluded. Appropriate notes will disclose when this is the case.

B.1.2 Imports Data

This dataset contains all the records that correspond to imports. Again, a line in this dataset can be read as an item (product as classified using the Harmonized Codes to the 6th digit) within a shipment from a *supplier* somewhere in the world and an importer or *manufacturer* in Bangladesh. As many shipments are multi-product, the dataset is more disaggregated than the level of the transaction.

Together with other relevant information, the most salient variables in this data contain identifiers for the importing firm and the country of origin of the shipment, a classification and description for the product, the statistical value of the product, its net mass in kilograms and characteristics of the shipment (mode of transport, terms of delivery, ports, countries, currency of invoice, exchange rate conversions, etc.).

The National Board of Revenue compiled the records coming from the different Custom Stations. After appending the data coming from the different sources, our dataset contains $6,546,504$ observations, of which 0.45% (29,309 lines) constitute partial duplications that are left in the base dataset. The treatment of these differs with the different uses we gave to the dataset, but in all the cases, our calculations are free from distortions induced by these duplications.

As with the exports dataset, the data before 2005 was considered of low quality, after poor comparisons with UN Comtrade sources and reports from BGMEA. However, the observations corresponding to 2003 - 2005 were left in the dataset, for the purpose of cross-checking some of our assumptions in the matching inputs-to-outputs procedure. The distribution of the oversations over years and custom offices look as follows:

Table B.3: Frequencies of Observations over Years, Imports Data

Year	Freq.	Percent	Cum.
2002	23	0	0
2003	6,257	0.1	0.1
2004	195,618	3	3.09
2005	412,461	6.32	9.42
2006	488,640	7.49	16.91
2007	520,804	7.98	24.89
2008	797,125	12.22	37.11
2009	1,044,918	16.02	53.13
2010	950,635	14.57	67.7
2011	1,279,179	19.61	87.31
2012	827,898	12.69	100
Total	6,523,558	100	

Source: Own Calculations.

Table B.4: Frequencies of Observations over Custom Stations, Imports Data

Station	Code	Freq.	Percent	Cum.
Dhaka	101	1,003,614	15.34	15.34
Dhaka-K	102	412,145	6.3	21.64
Chittagong House	301	3,744,752	57.23	78.87
Chittagong - EPZ	303	184,107	2.81	81.68
Chottagong Main	305	641,487	9.8	91.48
Mongla 1	501	22,480	0.34	91.83
Mongla 2	502	54	0	91.83
Benapole	601	534,691	8.17	100
	Total	6,543,330	100	

Source: Own Calculations.

As in the case of the exports, the non-EPZ Stations in Chittagong concentrate the vast majority of the observations. Data from these Custom Stations is available for the whole of the period of the panel. Unfortunately, for the rest of the Offices we face the following restrictions: (i) Dhaka Custom Offices (101 and 102) only report information from 2008 onwards; (ii) information coming from the EPZ in Chittagong is as well only available from 2008 until the end of the panel; (iii) like on the exports side, data coming from small custom offices is only available for part of the period covered (2008 and 2009 for 601 and 2010 - 2012 for Mongla).

Like on the exports side of the data, the most worrying restriction is that of the missing data from Dhaka before 2008, for the purpose of doing firm-level or relationship-level analysis over time exploiting the whole of the 2005 - 2012 period. Again, the garment manufacturers that we observe on the exports dataset tend to use one or the other (set of) Custom Station almost exclusively for their imported inputs. Exercises equivalent to those performed with the exports data at the importer level, by quarter, by year and over the whole of the panel, excluding the years for which data from any one of the stations was missing, confirmed this conclusion.

A potential issue of concern would be the missing data from Benapole. This is a Custom Station that deals with in-land commerce and it is almost fully dedicated to imports coming from India. The missing data before 2008 and after 2009 could be a problem if significant volumes of garment-relevant inputs were coming through this custom office. The product codes imported through Benapole over the period we observe correspond 87% of the times to categories that are not related to garment. The remaining 13% could potentially be related to garment (mainly chemicals and dying products) and half of the times, these imports correspond to firms we identify as garment exporters. For this reason, when working with the import-export matched data, we have accounted for the fact that some manufacturers might be sourcing via Benapole outside the observed 2008 - 2009.

As we are interested in the imports that are related to the RMG sector only, the universe of the imports into the country is not as relevant. To select the right product categories , all the imports undertaken by garment exporters (whose identities are obtained from the exports dataset) were analysed. All the product categories at two digits of aggregation that were imported by garment manufacturers were kept in the data, irrespective of the identity of the importer.

Of the 6.5 million observations in our data, less than 27% correspond to imports performed by our garment exporters. However, considering the universe of transactions in the product categories that the garment exporters import, we have almost 90% of the observations in the original dataset. For completeness, we keep all the product categories and flag the non-garment-relevant 10%+.

B.2 Variables Management and Transformations

B.2.1 Prices and Quantities

Statistical values for the shipments, both for exports and imports, are already present in the data. According to the information we obtained from the NBR, these statistical values are calculated using the data in the bill of entry or export directly: taking the FOB price, converted into BD Takas at an exchange rate that the Central Banks provided every month or daily, depending on the year. If no insurance is specified in the bill, it is computed as 1% of the FOB. Similarly, if freight is not included, it's computed as 1% over the (FOB + insurance). Landing charges are computed as 1% of (FOB + insurance + freight).

In the data, we always observe the *mode* of the transaction -i.e., FOB, CIF, CNF, etc.- , the value in the invoice and the currency of the invoice, the exchange rate and the statistical value. Using the details above, we were able to reconstruct one or other record (invoice or statistical value) consistently in the best part of the data.

For many of the calculations in this project, quantities and prices were winsorized transforming the top and bottom 0.5% of the quantities and values within each HS4 product category.

B.2.2 Alternative Product Classifications

At different points in this projects, for convenience and ease of exposition, imported inputs for the garment sector were re-classified using the information we had on the HS classifications, into categories according to the *material* of the input and the *type* of input. The following explains the re-classification procedure.

					TYPE											FABRIC		TRADE	PURITY		WEIGHT		FIBRE				
	Two Digits	Rank		Four Digits	Raw	Fibre	Yarn	Thread	Waste	Fabric	Parts	Garment	Packaging	Office supplies	Accesories	Woven	Knitted	Retail	High	Low	Heavy	Light	Natural	Synthetic	Artificial	Mixtures or other	Sixth digit
52	Cotton, yarns and fabrics	2	5209	5209 woven cotton fabrics, nu 85% cot, wt ov 200 g/m2						1						1			1		1		1				Bleached / Unbleached; Multiple / single colours ; Decitex measure ; Cotton proportion (for yarns); Dyed / Not Dyed; Printed / Not printed
		3	5208	5208 woven cotton fabrics, nu 85% cot, wt n/ov 200 g/m2						1						1			1			1	1				
		7	5211	5211 woven cotton fabrics, un 85% cot, mmfmix, ov 200g/m2						1						1				1	1		1			1	
		8	5212	5212 woven cotton fabrics nesoi						1						1			1	1	1	1	1				
		17	5205	5205 cotton yarn (not sewing thread) nu 85% cot no retail			1												1		1	1	1				
		21	5210	5210 woven cotton fab, un 85% cot, mmfmix, n/ov 200g/m2						1						1				1		1	1			1	
		29	5204	5204 cotton sewing thread, retail packed or not				1										1	1	1	1	1	1				
		37	5203	5203 cotton, carded or combed	1														1		1	1	1				
		44	5206	5206 cotton yarn (not sewing thread) un 85% cot no retail			1													1	1	1	1				
		48	5202	5202 cotton waste (including yarn waste etc.)					1										1	1	1	1	1				
		53	5207	5207 cotton yarn (not sewing thread) retail packed			1											1	1	1	1	1	1				
62	Woven apparel and accesories	1	6217	6217 made-up clothing access nesoi, garment etc parts nesoi											1												6217: parts vs accesories ; 6209: material (cotton, synthetic).
		58	6209	6209 babies' garments & accessories, not knit or croch								1															
96	**Miscellaneous manufactures articles**	**4**	**9606**	**9606 buttons, press studs etc, button mold & blanks etc**							**1**																**Material (plastic, metal, etc.)**
		6	**9607**	**9607 slide fasteners and parts thereof**							**1**																
		46	**9618**	**9618 tailors' dummies & other mannequins for display**							**1**																
55	Man made staple fibres, yarns and fabrics	11	5512	5512 woven fabric, synth staple fib nu 85% synth st fiber						1						1			1		1	1		1			Materials of mixtures; bleaching; dyeing.
		13	5513	5513 woven fabric, syn st fib un 85%, cot mix, n/ov170g/m2						1						1				1		1		1			
		14	5514	5514 woven fabric, syn st fib un 85%, cot mix, ov 170 g/m2						1						1				1	1			1			
		15	5516	5516 woven fabrics of artificial staple fibers						1						1			1	1	1	1			1		
		18	5515	5515 woven fabrics of synthetic staple fibers nesoi						1						1			1	1	1	1		1			
		27	5509	5509 yarn (no sew thread), syn staple fib, not retail			1												1	1	1	1		1			
		36	5501	5501 synthetic filament tow		1													1	1	1	1		1			
		39	5511	5511 yarn (no sew thread), manmade staple fiber, retail			1											1	1	1	1	1		10& 20	30		
		47	5510	5510 yarn (no sew thread), art staple fib, not retail			1												1	1	1	1			1		
48	**Paper and paperboard**	**5**	**4821**	**4821 labels of paper or paperboard, printed or not**									**1**														**Not relevant**
		45	**4823**	**4823 paper, paperboard, cellulose wad to size & arts nesoi**									**1**														
		52	**4811**	**4811 paper, paperboard, wad etc, coat etc nesoi, roll etc**									**1**														
		65	**4819**	**4819 cartons etc paper, office box files etc, paper etc**										**1**													
		67	**4818**	**4818 toilet paper, paper tissues, towels, napkins etc**										**1**													

FIGURE B.1: Reclassification of Relevant Imported Inputs - Part I

					TYPE											FABRIC		TRADE	PURITY		WEIGHT		FIBRE				
Two Digits		Rank	Four Digits		Raw	Fibre	Yarn	Thread	Waste	Fabric	Parts	Garment	Packaging	Office supplies	Accessories	Woven	Knitted	Retail	High	Low	Heavy	Light	Natural	Synthetic	Artificial	Mixtures or other	Sixth digit
60	Knitted or crochetted fabrics	10	6001	Pile fabrics, including "long pile" fabrics and terry fabrics, knitted or crocheted.						1							1						21& 91	22& 92	22& 92	10& 29% 99	Fabric (synthetic, cotton, artificial,
		16	6006	Other knitted or crocheted fabrics.						1							1						1x&2 x	3x	4x	9x	
		19	6002	Knitted or crocheted fabrics of a width not exceeding 30 cm, containing by weight 5 % or more of elastomeric yarn or rubber thread, other than those of heading 60.01.						1							1									all	
		33	6005	Warp knit fabrics (including those made on galloon knitting machines), other than those of headings 60.01 to 60.04.						1							1						2x	3x	4x	5x	
		35	6003	Knitted or crocheted fabrics of a width not exceeding 30 cm, other than those of heading 60.01 or 60.02.						1							1						10& 20	30	40	90	
54	Man made filaments, yarns and fabrics	9	5407	5407 woven fab of syn fil yarn, incl monofil 67 dec etc						1						1								1			Material of the filament (polyester, viscose, etc.)
		26	5402	5402 synthetic filament yarn (no sew thread), no retail			1																	1			
		30	5408	5408 woven fab of art fil yarn, incl monofil 67 dec etc			1																		1		
		32	5401	5401 sewing thread of manmade filaments, retail or not				1																10	20		
		43	5403	5403 artificial filament yarn (no sew thread), no retail			1																		1		
58	Special woven fabrics	12	5807	5807 labels, badges etc of textiles, in the pc etc									1														Material (cotton, wool, synthetic, artificial, etc.)
		22	5801	5801 woven pile & chenille fabrics nesoi (no terry etc)						1						1							10& 2x			rest	
		31	5806	5806 narrow woven fabrics except labels etc in pc etc						1						1							31	32	32	10& 20&	
		34	5809	5809 woven fabrics of metal thread & metallized yarn nec						1						1										all	
		40	5804	5804 tulles & other net fabrics, lace in pc, strip etc.						1						1										all	
		42	5802	5802 woven terry fabrics nesoi, tufted tex fabric nesoi						1						1										all	
		51	5803	5803 gauze (other than narrow fabrics not over 30 cm)						1						1										all	
39	**Plastics and platic articles**	**23**	**3923**	**3923 containers (boxes, bags etc), closurers etc, plast**									**1**														**Plastic content. Not relevant.**
		24	**3926**	**3926 articles of plastics (inc polymers & resins) nesoi**										**1**	**1**												
		28	**3919**	**3919 self-adhesive plates, sheets, film etc of plastics**										**1**													
		41	**3916**	**3916 monofil, cr-sect ovimm, rods, sticks etc, plastics**										**1**	**1**												
		49	**3921**	**3921 plates, sheets, film, foil & strip nesoi, plastics**										**1**	**1**												
		50	**3920**	**3920 plates, sheets, film etc no ad, non-cel etc, plast**										**1**	**1**												
59	Impregnated, coated or laminated fabrics	20	5903	5903 textile fabrics (not tire cord) coat etc, plastics						1						1									1		Type of process (coated, rubberized, covered, etc.)
		38	5906	5906 rubberized textile fabrics, other than tire cord						1						1	1								1		
		55	5907	5907 textile fabric, coated, etc, theatrical scenery, back-cloths						1						1									1		
51	Wool and animal furs, yarns and fabrics	25	5111	5111 woven fabrics of carded wool or fine animal hair						1						1			1				11& 19			20& 30& 90	Type of wool, mixture, etc.
		56	5109	5109 yarn of wool or fine animal hair, for retail sale			1											1	1				1				
		61	5101	5101 wool, not carded or combed	1														1				1				
		69	5103	5103 waste of wool or of fine or coarse animal hair					1										1				1				
		70	5105	5105 wool & fine or coarse animal hair, carded & combed	1														1				1				

FIGURE B.2: Reclassification of Relevant Imported Inputs - Part II

B.2.3 Firm Identifiers

As explained above, one of the more salient feature of the datasets we work with is that we observe the identities of both parties in trade, in the case of the exports and the identity of the importing firm, in the case of the imports.

B.2.3.1 Sellers' Identities

The dataset, as constructed from the records in the Custom Offices, identify the exporters using the Business Identification Number (BIN) of the firm. This constitutes a 10 (or 11, in the new system) digits number. The first digit corresponds to the Commissioner to which the productive activity is settled (not the administrative location). Firms that have productive activities in two different locations corresponding to different Commissioners are assigned one of the two by the National Board of Revenue, according to the size of the business in each location. Each Commissioner is divided into circle offices (for example, in Dhaka there are around 30 circles) and the second and third digits in the code correspond to the circle in which the productive activity of the firm is located. The fourth digit corresponds to the tax category of the firm, according to its yearly turnover. This is re-assessed at the end on each fiscal year, which might lead to changes in the BIN number for the firm (the whole number changes, not only this digit). The main categories are 1: VAT, 2: Turnover, 3: Small Cottage Industry, 4: Others. Digits five to nine are the actual firm identifier within the National Board of Revenue (NBR) and it is assigned by the circle processing the application. The tenth digit is a number coming from a random numbers generator to avoid duplications.

The main complication of using BINs as firm identifiers was that the firm code (digits 5 to 9) is not necessarily unique across plants under the same ownership structure. One ownership structure might register different divisions within the same firm under different BINs, for tax purposes, inducing misidentification of the sellers. Moreover, the same plant could potentially have - completely - different BIN codes over time, if its turnover bracket or location change. Therefore, over time a firm whose essential characteristics remain unchanged might change BINs to obtain tax incentives or fall under special subsidies schemes offered by the government. The information in our *raw* data didn't allow us to spot one or the other misidentification issue.

We dealt with these two concerns in five ways, generating an alternative (to BIN codes) firm identifier that was used in the study for robustness checks.

First, using data (up until 2010 only) from the VAT Office within NBR, each BIN number in our dataset was matched with the name of the firm, its address and contact details. Whenever two different BIN codes were matched with the same firm name and address, these were unified to be considered the same firm.

Second, we matched the BINs in our dataset with the database that Bangladesh Customs holds on updates of BIN codes for all the exporters and importers. In this dataset, each entry contains an *old* BIN code, a *new* BIN code, the name and address of the firm. Most of the code migrations are associated to switches from 10 digits to 11 digits codes. We crosscheck the information in this database with our dataset and there's an overlap of 110 firms, whose identities are unified as appropriate. However, these coincide with unifications done in the previous step.

Third, we were able to crosscheck our data with the lists of Members and Associate Members of the Association of RMG Exporters. The Association is the competent authority for processing the necessary applications for export / import permissions and tax reliefs, so they maintain accurate records of the identities of the exporters, including ownership data in some cases. Woven sellers outside Export Processing Zones are bound to be registered with the Association, while knitwear-only exporters and the small fraction of firms in Export Processing Zones can also use other channels for exporting / importing (BKMEA and BEPZA). Using the data from the Association, the original number of 7033 distinct sellers observed in the panel before September 2010 was brought down to 6027 firms. The identification of firms was done in stages using the correspondence between BINs and internal codes of the Association, matches in the names and addresses and coincidences in the BINs and documents produced in the applications for exports permissions. This procedure was found to unify within the same identifier, different BINs exporting at the same time and different BINs over time.

Fourth, we used the Bond Licence Numbers in the dataset we obtained from the BOND Commissionaire to unify BIN numbers that held the same Bond Licence, as plants that share bonded warehouse facilities under the same licence are typically part of the same ownership structure.

Finally, we explored the trajectories of all the firms appearing in the panel within a suitable time-window after a seller drop out [2] . The idea of the exercise was to check whether the characteristics and trading patterns of a new firm were *similar enough* to those of a dropping seller, to suggest they could actually be the same firm. The key aspects that were analyzed were the timing of the death and births, the location of the firms, the main products and volumes exported and the main buyer for each of these.

[2]Time windows were set at 1 month, 3 months, 6 months and 9 months and finally using the mean/-median with two standard deviations / median absolute deviations of the gap between transactions for the dropping firm.

Using these criteria with different weights assigned to each factor, we found no strong evidence to impute the same identity to any two firms.

As a result of the steps above, we have the BIN codes as *conservative* plant identifiers and an alternative identifier for the firms using the unifications above. Most of the exercises done using this data were carried out using both identifiers, as a robustness check. For the purpose of these project, when not specified otherwise, we will refer to a firm or a plant as units identified with their BINs.

B.2.3.2 Buyers' Identities

At the most downstream level, we have information on the firms located elsewhere buying ready-made garment from Bangladesh. Strings containing names and addresses of these firms - buyers from now on- where introduced manually in the system that originated our data. Spelling mistakes, varying criteria across Custom Offices or over time and differences in administrative procedures induced difficulties in the mapping of transactions to well delimited unique buyers. Using the names recorded as identifiers, the raw data contained nearly 340,000 different buyers pooling all the years together. After a *cleaning* procedure focussed on correcting the mistakes mentioned above, the list went down to about 7,000 different buyers and a pool of small firms collected in a broad category of firms for which the cleaning was not possible.

The *cleaning* procedure was done in stages.

First, using the uncleaned strings, the names of the (almost) 1,000 largest buyers were manually cleaned.

Second, using these strings, one relevant substring was chosen for each of them and the whole of the data was scanned to find matches in the uncleaned strings [3]. In this procedure, almost 80% of the matches were unique and, after the relevant controls, the names were corrected. the multiple matches cases were analysed one by one and, when suitable, replacements were introduced accordingly.

Third, the remaining uncleaned strings were modified to discard strange characters and unify expressions such as "INT.", "INTL.", "INTERNATIONAL", etc.. The scanning routine was performed again over these modified strings.

Fourth, from the remaining uncleaned lines, the largest (almost) 1,000 buyers were selected and the first and third steps were repeated. Fifth, with now 2,000 identified clean

[3] When the clean name of the firm wouldn't render a compelling substring, the related uncleaned strings were leaned manually. A - fictitious - example of this would be a clean name like "THE COMPANY INC.", whose possible substrings would generate matched with clearly unrelated firms.

names, the remaining uncleaned strings were scanned now allowing for: (i) a spelling mistake involving one character only (including one missing or one extra character); (ii) one parsing mistake, involving one extra or one missing space only; (iii) two parsing mistakes of any kind; (iv) a character swapping, involving two characters; (v) combinations of (i) and (ii); (vi) combinations of (i) and (iii); combinations of (iii) and (iv); combinations of (iv) and (i). The more conservative scans performed really well, allowing for corrections in most of the remaining uncleaned lines. Criteria (v) and above produced multiple potential matches and only 15% of these were used to introduce corrections. At this stage, about 90% of the lines in the exports dataset ad a clean name for the buyer. Robustness checks of these stage were performed exploiting the buyers addresses and a soundex, to identify matches of names that "sounded" similar.

Fifth, a large number of line-by-line corrections were introduced, using a *.do* file that contains over 100,000 replacement statements.

Sixth, the denominations in the Euromonitor Data were used to unify identities that showed in our data sometimes using local denominations of a brand, global denominations of a brand, national denominations of the firm or group or the name of the parent company in cases of joint ownership.

Seventh, publicly available company reports of the 15 largest buyers were explored to correct identities of firms in the presence of mergers and acquisitions. Using this source of information, 9 relevant changes were introduced.

Eigth, for the top 100 buyers, the patterns of trade were observed, with special focus on the volumes of trade, product categories and destination of the shipment to spot miss-imputations.

As a result of these steps, 96% of the lines in the exports dataset, explaining 97% of the traded values, have a *clean* name for the buyer.

B.3 Comparison with Comtrade Data

To better assess the representativeness and robustness of the coverage of our main datasets, we compared our records to those in the UN Comtrade database[4].

In broad terms, disagreement with UN Comtrade Data is expected to occur due to a number of reasons:

[4]DESA/UNSD, United Nations Comtrade database.

- After received from the national authorities, data is standardized by the UN Statistics Division, using Comtrade standardization protocols that can induce discrepancies with the data we have from the National Board of Revenue.
- The Comtrade data might feature records coming from different sources of information.
- In the Comtrade data values of disaggregated commodities do not necessarily sum up to the total trade value at higher levels of aggregation. This is mainly due to potential restrictions in disclosure from the reporting country.
- The time-wise coverage of our data and that in Comtrade differs.
- Our data comprises records of the largest Custom Offices but not the Universe of trade with Bangladesh.
- Product classification criteria might differ.

More specifically, the only overlap our panel has with the data available in the UN Comtrade database is for years 2005 to 2007[5]. Also, the Explanatory Notes in the Bangladesh section of the Comtrade search engine reports that all the data corresponding to 2005 and 2006 for Bangladesh was obtained from FAO, while that of 2007 has the Bangladesh Bureau of Statistics as ultimate source of data.

All the three years are presented by Comtrade with a note stating that "Data for this year has been re-processed to make correction to the data". All the imports are reported CIF and exports are reported FOB. While our data features the Customs daily (or monthly in some cases) exchange rates to convert foreign to local currencies or viceversa, Comtrade data uses a fixed currency conversion rate (from Bangladesh Takas to US Dollars) is used for each year, according to the following rates:

Table B.5: Currency Conversion Table, Comtrade Database (BDT to USD)

	Flow	
Year	Import	Export
2005	0.015544	0.015539
2006	0.014493	0.014495
2007	0.014521	0.014521

Source: DESA/UNSD, United Nations Comtrade database, Explanatory Notes and Publications.

[5]As explained above, our records before 2005 were considered of low quality and not used for any part of our analysis, except when stated in the procedure of matching inputs and outputs.

For the purpose of the comparisons of values, we unified the exchange rate conversions to use those reported by Comtrade, to avoid discrepancies induced by currency rates.

Product classifications also show minor mismatches when data from both sources are matched at the product - time levels. When the match is performed at 6 digits of aggregation in the HS codes (2002 or as reported), there are three product categories (611512, 611520, 611691) that are present in the Comtrade Data and that we don't have in the Customs Data (for years 2005 or 2006) and there are other codes (610310, 611510, 611522, 611529 , 611530, 611594, 611595, 611596) in the Customs Data (2007 only) that don't show in the Comtrade Database.

An additional source of discrepancy in the comparison of volumes is that 98% of the data obtained from the Comtrade dataset has the traded volumes (in kilograms) estimated, possibly from the quantities traded reported in an alternative measurement unit. No details on the estimation procedure are available, but it can be seen below that while the comparisons of volumes recorded in both Datasets looks very weak, that in values performs relatively well. This might be evidence of discrepancies of information across sources due to the manipulation of quantities in the Comtrade data.

Given that the Comtrade at different aggregation levels doesn't necessarily match, the comparisons at 4 digits are done using the reported UN Comtrade data rather than the aggregation of the subcategories. Only when the data at four digits is not available, the aggregation of six digits categories is used.

B.3.1 Exports

The following histograms show the distribution of ratios in traded values (US dollars) as reported in Comtrade Data to that reported in our Customs Data. Ratios below one imply higher values reported in the Customs data.

FIGURE B.3: Histogram of Ratio of Values Comtrade/Customs per $HS6$ - Woven

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

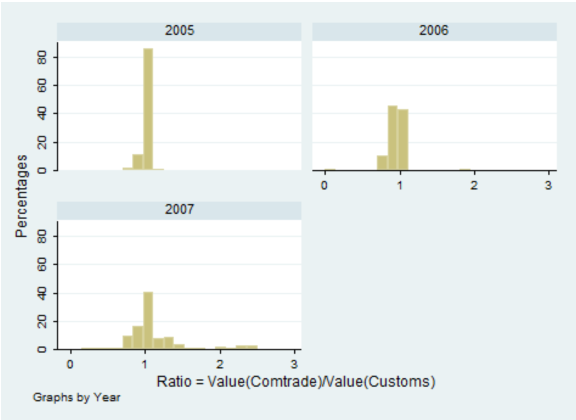


FIGURE B.4: Histogram of Ratio of Values Comtrade/Customs per $HS6$ - Knit

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

The tables below show the ratios for each product category and year combination. The tables that correspond to volume ratios are omitted (available on request) and tables with ratios in values are presented.

The comparison was done at six digits of disaggregation. In the interest of space, I present here the comparison up to the fourth digit of aggregation only.

TABLE B.6: Ratio of Exported Values (USD, Comtrade currency conversion) Comtrade Data / Customs Data: Four Digits Codes

	Year			
HS4	2005	2006	2007	Total
6101	0.991	0.912	0.955	0.953
6102	0.863	0.957	0.976	0.932
6103	0.957	0.938	0.984	0.960
6104	0.986	0.911	1.285	1.061
6105	0.999	0.919	0.943	0.954
6106	0.996	0.909	0.883	0.929
6107	0.995	0.946	1.020	0.987
6108	0.971	0.951	2.400	1.441
6109	1.002	0.904	0.896	0.934
6110	0.988	0.975	0.990	0.984
6111	0.994	0.857	0.954	0.935
6112	1.000	0.902	0.924	0.942
6113	0.984	0.988	1.292	1.088
6114	1.001	0.888	0.800	0.896
6115	1.000	0.932	0.957	0.963
6116	0.999	1.018	1.000	1.006
6117	1.000	0.979	1.495	1.158
6201	0.932	0.944	1.088	0.988
6202	0.883	0.926	1.024	0.944
6203	0.966	0.927	0.978	0.957
6204	0.964	0.916	1.024	0.968
6205	0.992	0.936	0.907	0.945
6206	1.004	0.919	1.009	0.977
6207	0.976	0.945	0.976	0.965
6208	0.996	0.952	1.048	0.999
6209	0.965	0.956	0.912	0.945
6210	1.014	0.986	1.168	1.056
6211	0.961	0.862	1.061	0.961
6212	0.903	0.926	0.913	0.914
6213	1.000	0.953	1.370	1.108
6214	1.000	0.960	1.351	1.104
6215	1.001	0.609	1.876	1.162
6216	0.998	0.950	0.996	0.981
6217	0.978	0.953	1.346	1.092

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

The time lines that follow plot the volumes and values, in kilograms and dollars, respectively for knitwear and woven. Line graphs on volumes are presented first.

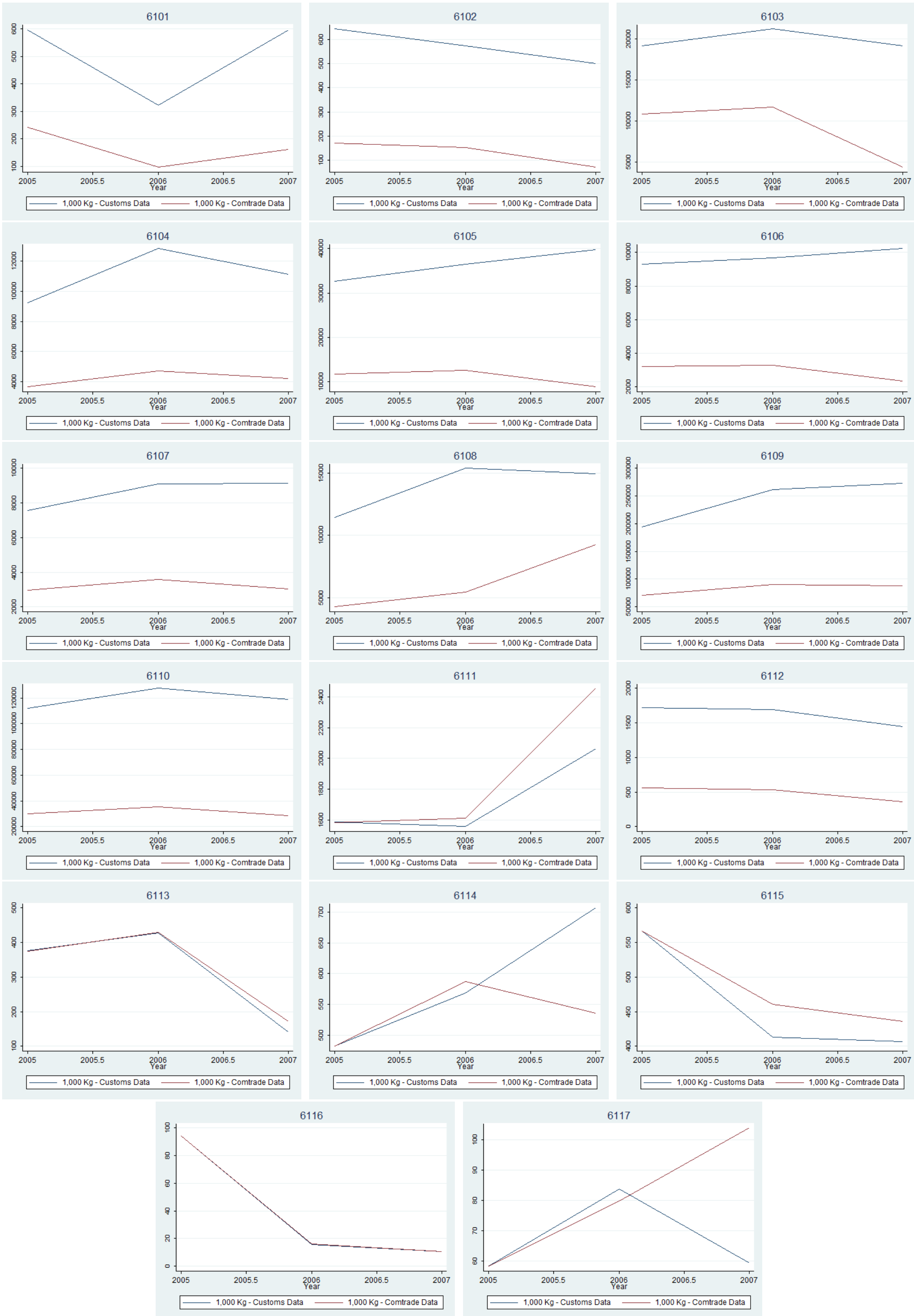


FIGURE B.5: Evolution of Volumes - HS4 Knitwear

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

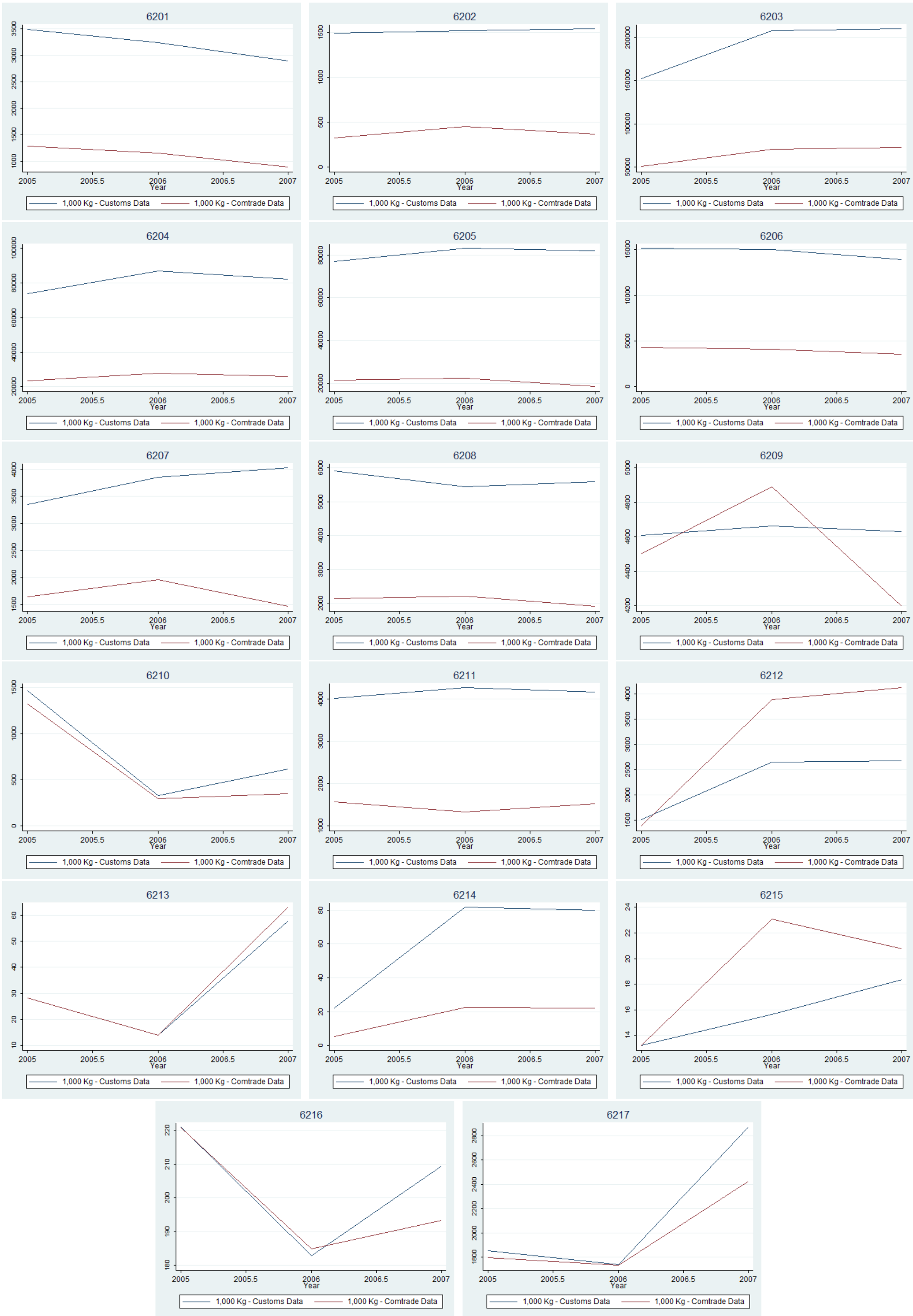


FIGURE B.6: Evolution of Volumes - HS4 Woven

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

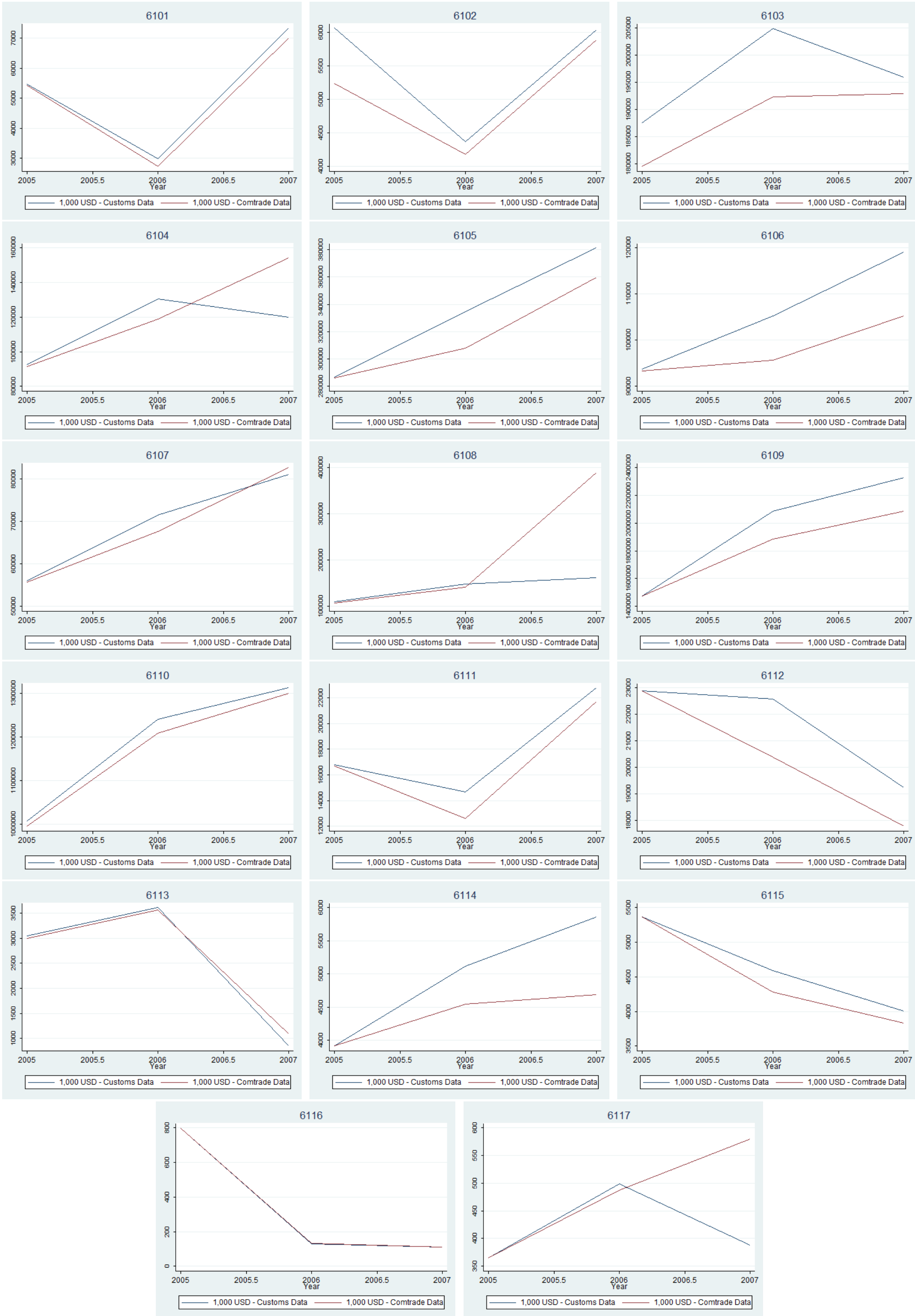


Figure B.7: Evolution of Values - HS4 Knitwear

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

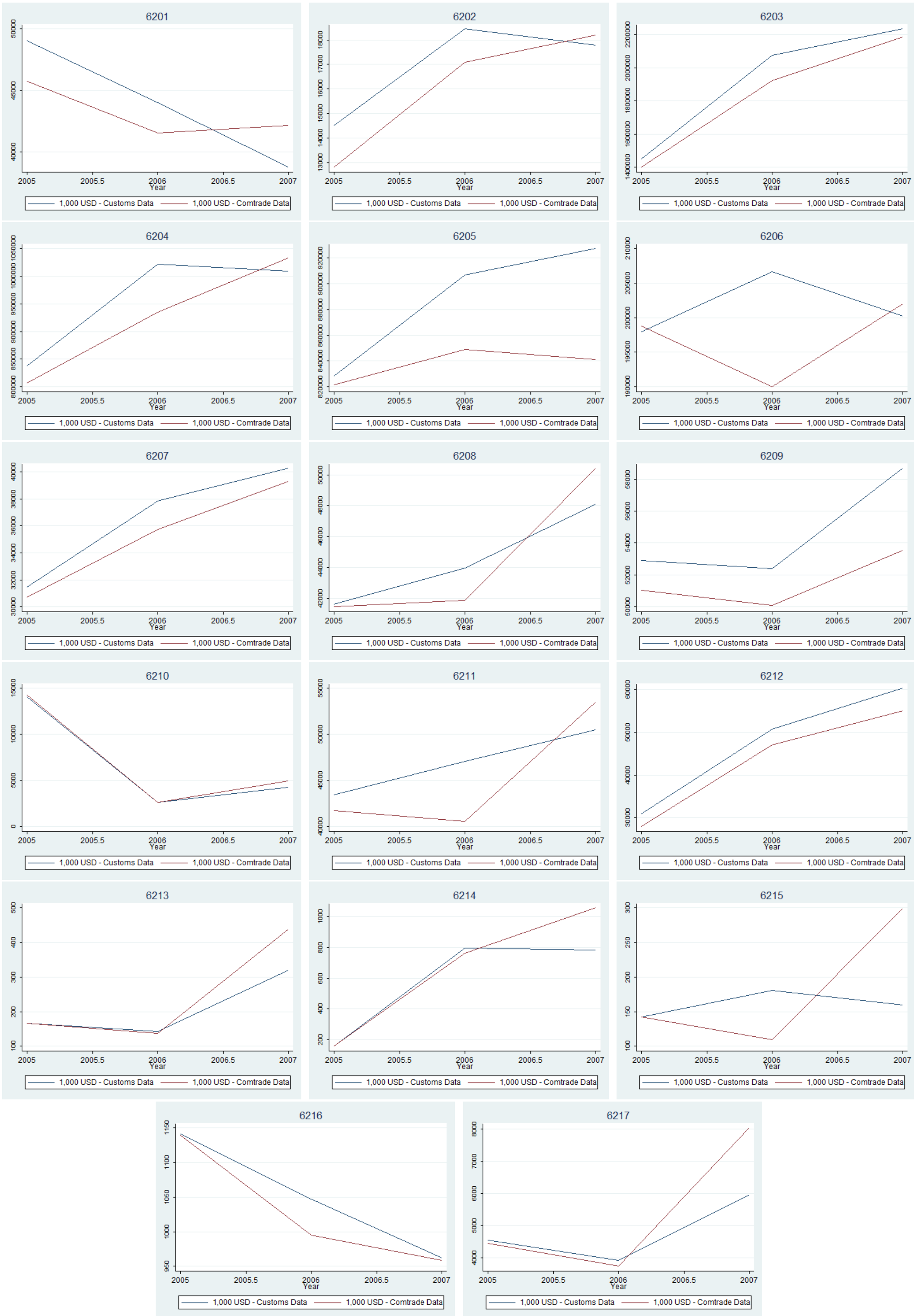


FIGURE B.8: Evolution of Values - HS4 Woven

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

For reference for the above graphs, what follows shows the relevance of each product category in the broad garment sub-sector. The y-axis measures the exports (kilograms) of a given HS4 product, grouped by sub-sectors (knit or woven), in years from 2005 to 2007 period. The first graph is done using Comtrade Data, while the second one is done using Customs Data.

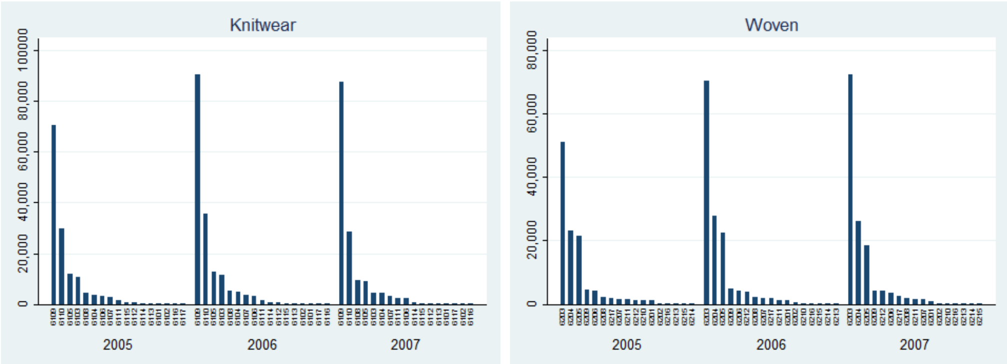


FIGURE B.9: Relative Sizes of HS4, Woven and Knit - Comtrade

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

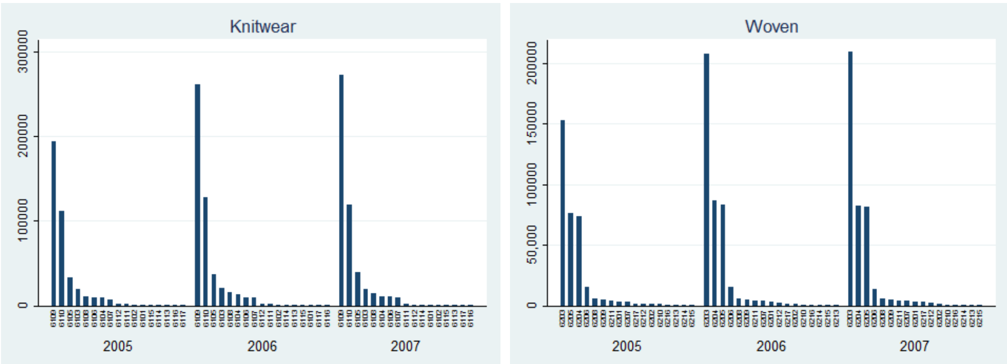


FIGURE B.10: Relative Sizes of HS4, Woven and Knit - Customs

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

B.3.2 Imports

On the imports side, as we are only interested in the imports that are used as inputs for the garment sector, I only compare the most relevant product categories that correspond to fabric or alternative "basic" inputs for the sector. For the selection of import categories, I extract BIN numbers of the exporters in the Customs dataset and merge with the imports data at the sellers level. More than two thirds of the garment exporters import at least one type of basic input. These are ranked according to the exported volumes over the panel and the top three categories at the 2-digits level are selected for the comparison.

At six digits, the comparison between sources of data looks poor, product-by-product. Aggregation at four digits show a slightly better match between data sources, possibly explained by differences in nomenclature assignments. Although there are some product categories that show a very high or very low ratio, both in values and volumes, it can be seen in the bar graphs that the most relevant products show a reasonable comparison of the two sources of data.

Additional limitations in our Customs data for the years 2005-2007 might induce poor results in this comparison. As explained, our Customs Data is available only for one of the custom offices (301, Chittagong) for this period in the Imports data.

Table B.7: Ratio of Net Weight (KG) Comtrade Data / Customs Data

	Year of Declaration			
HS4	2005	2006	2007	Total
5201	1.014	1.118	1.204	1.112
5202	0.935	0.276	1.163	0.791
5203	1.890	1.788	1.247	1.642
5204	6.823	0.793	8.070	5.229
5205	0.715	0.589	0.728	0.677
5206	1.044	0.883	0.860	0.929
5207	0.792	2.216	1.652	1.553
5208	0.681	0.249	0.372	0.434
5209	0.662	0.335	0.447	0.481
5210	0.673	0.507	0.704	0.628
5211	0.957	0.080	0.203	0.413
5212	0.548	0.028	0.106	0.227
5801	1.385	0.948	1.881	1.405
5802	0.960	2.463	8.076	3.833
5803	54.371	0.987		27.679
5804	13.341	3.348	18.742	11.810
5806	1.993	2.320	3.939	2.751
5807	8.178	3.280	7.684	6.381
5808	1.365	11.055	1.678	4.699
5809	0.524	0.002	0.002	0.176
5810	0.948	0.636	0.030	0.538
5811	2.863	2.857	1.339	2.353
6001	0.793	0.225	0.333	0.451
6002	0.609	0.049	0.139	0.266
6003	0.515	0.090	0.138	0.247
6004	0.376	0.005	0.292	0.224
6005	1.757	6.792	3.539	4.029
6006	0.671	1.394	3.139	1.735

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

For reference for the above tables, what follows shows the relevance of each product category in the group of selected main inputs. The y-axis measures the values of the imports aggregated over all years from 2005 to 2007 period. The first graph is done using Comtrade Data, while the second one is done using Customs Data.

Table B.8: Ratio of Imported Values (USD, Comtrade currency conversion) Comtrade Data / Customs Data

	Year of Declaration			
HS4	2005	2006	2007	Total
5201	1.079	1.162	1.228	1.156
5202	0.759	0.137	0.649	0.515
5203	1.237	1.013	1.248	1.166
5204	3.882	0.527	4.036	2.815
5205	0.679	0.516	0.615	0.603
5206	1.091	0.825	0.854	0.923
5207	0.871	2.273	1.405	1.516
5208	0.647	0.172	0.284	0.368
5209	0.665	0.301	0.385	0.450
5210	0.691	0.443	0.533	0.556
5211	1.048	0.110	0.214	0.457
5212	0.540	0.028	0.085	0.218
5801	0.764	0.603	1.050	0.805
5802	0.940	0.889	4.031	1.953
5803	114.314	1.486		57.900
5804	20.782	6.335	28.097	18.405
5806	1.756	1.462	2.588	1.935
5807	3.250	1.462	2.066	2.259
5808	1.756	6.832	0.394	2.994
5809	0.513	0.007	0.002	0.174
5810	1.025	0.692	0.033	0.583
5811	2.536	2.392	1.263	2.064
6001	0.567	0.144	0.196	0.302
6002	0.613	0.046	0.119	0.259
6003	0.508	0.070	0.098	0.225
6004	0.338	0.003	0.187	0.176
6005	1.251	3.622	1.757	2.210
6006	0.688	1.880	3.705	2.091

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

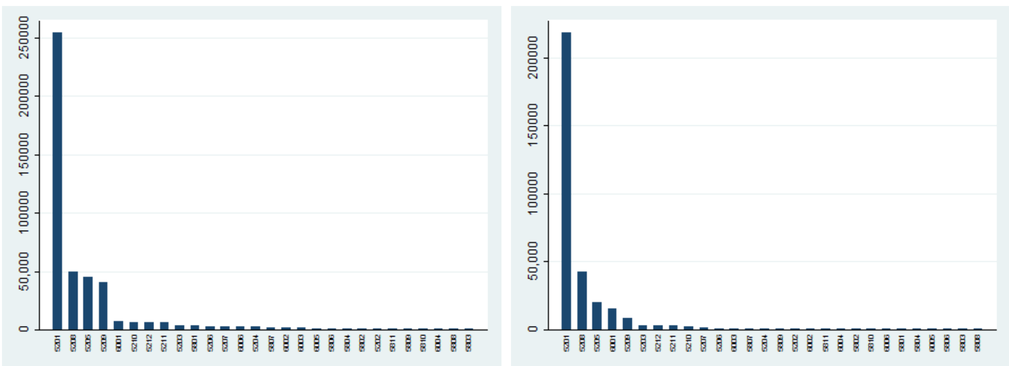


Figure B.11: Relative Sizes of HS4, Woven and Knit - Comtrade

Source: Own calculations using DESA/UNSD, United Nations Comtrade database.

Appendix C

Additional Descriptives of the Sector

The following sections contain tables and graphs with general descriptives that are referred to in the main text.

C.1 Descriptives on the International Context

Table C.1: Percentage of Garment Imports Flow to US, 2010

Country	Percentage
China	39.85
Vietnam	8.03
Bangladesh	5.37
India	4.42

Table C.2: Percentage of Garment Imports Flow to EU, 2010

Country	Percentage
China	45.53
Turkey	12.58
Bangladesh	9.37
India	6.76

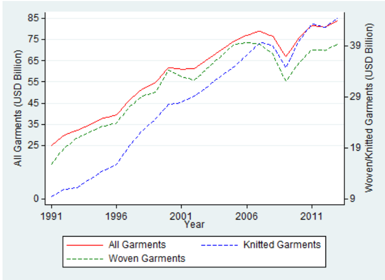


FIGURE C.1: Import Flow of Garments from World to US, 1991-2013 (COMTRADE)

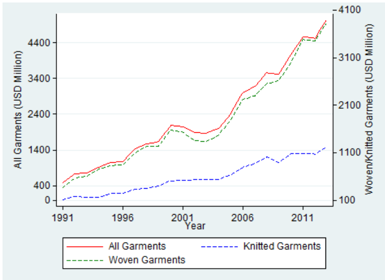


FIGURE C.2: Import Flow of Garments from Bangladesh to US, 1991-2013 (COMTRADE)

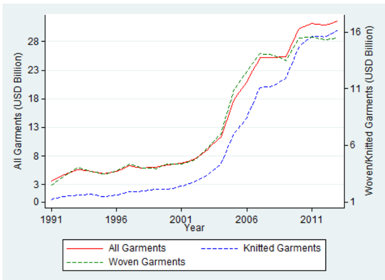


FIGURE C.3: Import Flow of Garments from China to US, 1991-2013 (COMTRADE)

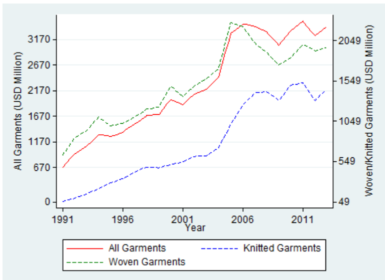


FIGURE C.4: Import Flow of Garments from India to US, 1991-2013 (COMTRADE)

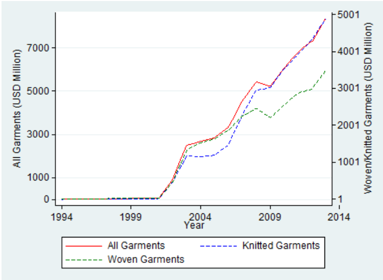


FIGURE C.5: Import Flow of Garments from Vietnam to US, 1994-2013 (COMTRADE)

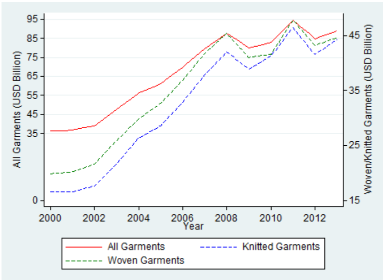


FIGURE C.6: Import Flow of Garments from World to EU, 2000-2013 (COMTRADE)

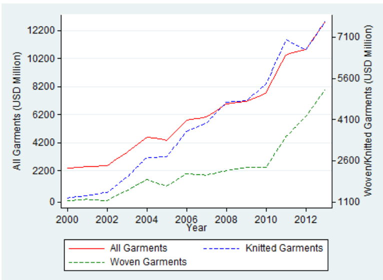


FIGURE C.7: Import Flow of Garments from Bangladesh to EU, 2000-2013 (COMTRADE)

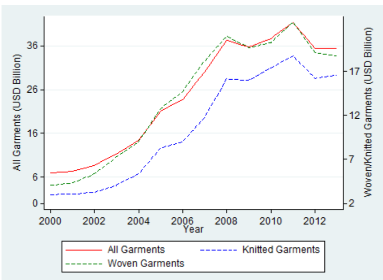


FIGURE C.8: Import Flow of Garments from China to EU, 2000-2013 (COMTRADE)

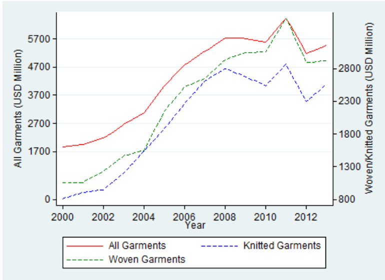


Figure C.9: Import Flow of Garments from India to EU, 2000-2013 (COMTRADE)

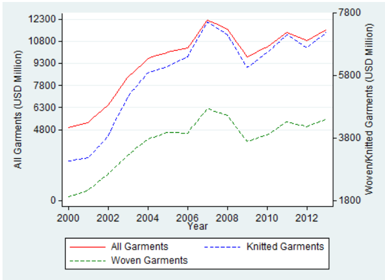


Figure C.10: Import Flow of Garments from Turkey to EU, 2000-2013 (COMTRADE)

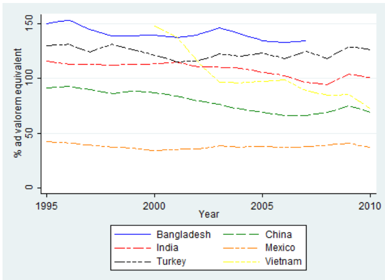


Figure C.11: International Trade Costs in US Manufacturing (ESCAP-WB)

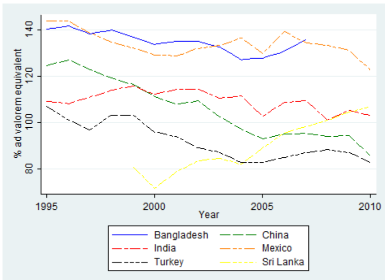


Figure C.12: International Trade Costs in UK Manufacturing (ESCAP-WB)

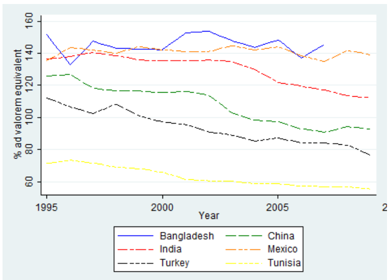


Figure C.13: International Trade Costs in France Manufacturing (ESCAP-WB)

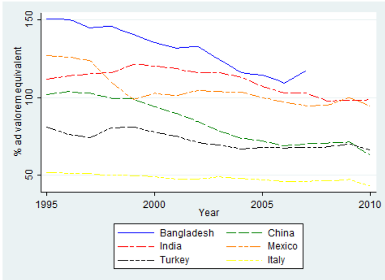


FIGURE C.14: International Trade Costs in Germany Manufacturing (ESCAP-WB)

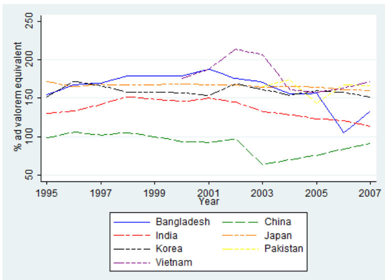


FIGURE C.15: International Trade Costs in Bangladesh Manufacturing (ESCAP-WB)

C.2 Exporter Dynamics - World Bank Data

Table C.3: Exporter Dynamics - Bangladesh I (World Bank Data)

All Garments (HS 61+62) - Bangladesh							
Year	2005	2006	2007	2008	2009	2010	2011
Number of Exporters	4,623	5,095	5,105	6,055	6,312	6,529	6,565
Number of Entrants		1,464	1,350	1,958	1,783	1,781	1,718
Number of Exiters		992	1,340	1,008	1,526	1,564	1,682
Export Value per Exporter: Median (thousand USD)	592.61	713.29	464.43	510.67	405.62	442.49	536.85
Export Value per Exporter: First Quartile (thousand USD)	67.86	75.64	67.77	69.59	54.41	60.55	71.69
Export Value per Exporter: Third Quartile (thousand USD)	2,904.15	3,775.61	2,353.89	3,082.91	3,024.30	3,382.04	4,314.79
Unit Price per Exporter: Median	16.98	17.56	19.36	20.25	20.13	20.99	27.02
Unit Price per Entrant: Median		15.20	16.91	17.81	16.56	18.74	23.11
Unit Price per Exiter: Median		14.08	15.14	15.92	17.55	16.43	17.04
Export Value per Entrant: Median (thousand USD)		67.82	68.46	71.90	47.33	56.66	57.20
Export Value per Exiter: Median (thousand USD)		38.38	50.07	43.36	55.97	43.84	44.90
Herfindahl-Hirschman Index	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Share of top 1% Exporters in TEV (Total Export Value)	0.33	0.35	0.39	0.40	0.43	0.43	0.42
Number of HS6 Products per Exporter: Median	6	5	5	5	4	4	4
Number of Destinations per Exporter: Median	5	5	4	4	4	4	4
Firm Entry Rate		0.58	0.53	0.65	0.57	0.55	0.53
Firm Exit Rate		0.44	0.53	0.40	0.51	0.50	0.52
Firm Survival Rate		1.10	1.36	1.19	1.15	1.10	
2-year Firm Survival Rate		0.80	1.00	0.84	0.79		
3-year Firm Survival Rate		0.63	0.82	0.66			

We are aware of the inconsistency in the figures reported as firm survival rates and we treat these figures with caution. For completeness and as referred in the main text, all statistics on the selected indicators are computed and presented as offered in the World Bank Database.

Table C.4: Exporter Dynamics - Bangladesh II (World Bank Data)

Men's Woven Suits and Ensembles (HS 6203) - Bangladesh							
Year	2005	2006	2007	2008	2009	2010	2011
Number of Exporters	1,249	1,472	1,393	1,673	1,774	1,861	1,894
Number of Entrants		541	406	624	608	626	616
Number of Exiters		318	485	344	507	539	583
Export Value per Exporter: Median (thousand USD)	216.02	243.19	172.37	200.53	158.31	168.58	194.97
Export Value per Exporter: First Quartile (thousand USD)	29.44	33.58	29.64	32.16	23.52	28.71	34.64
Export Value per Exporter: Third Quartile (thousand USD)	943.00	1,213.09	911.66	1,191.42	1,204.07	1,122.28	1,570.77
Unit Price per Exporter: Median	8.90	9.14	9.76	10.34	10.28	10.56	13.38
Unit Price per Entrant: Median		8.70	8.91	10.07	9.29	9.75	12.21
Unit Price per Exiter: Median		8.20	8.67	8.23	9.81	9.22	9.57
Export Value per Entrant: Median (thousand USD)		37.03	29.34	39.04	26.35	27.19	35.96
Export Value per Exiter: Median (thousand USD)		22.23	32.24	23.16	31.31	22.15	26.91
Herfindahl-Hirschman Index	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Share of top 1% Exporters in TEV (Total Export Value)	0.18	0.20	0.23	0.21	0.21	0.23	0.24
Number of HS6 Products per Exporter: Median	2	2	2	2	1	1	1
Number of Destinations per Exporter: Median	2	2	2	2	2	2	2
Firm Entry Rate		0.37	0.29	0.37	0.34	0.34	0.33
Firm Exit Rate		0.25	0.33	0.25	0.30	0.30	0.31
Firm Survival Rate		0.47	0.57	0.52	0.50	0.48	
2-year Firm Survival Rate		0.33	0.42	0.35	0.32		
3-year Firm Survival Rate		0.24	0.32	0.27			

Table C.5: Exporter Dynamics - Bangladesh III (World Bank Data)

Women's Woven Suits and Ensembles (HS 6204) - Bangladesh							
Year	2005	2006	2007	2008	2009	2010	2011
Number of Exporters	1,078	1,164	1,056	1,321	1,323	1,435	1,403
Number of Entrants		413	339	551	466	532	489
Number of Exiters		327	447	286	464	420	521
Export Value per Exporter: Median (thousand USD)	131.15	169.29	127.32	128.63	132.79	118.47	145.45
Export Value per Exporter: First Quartile (thousand USD)	23.28	29.40	22.79	28.40	27.59	25.35	31.50
Export Value per Exporter: Third Quartile (thousand USD)	599.63	762.34	502.36	612.06	662.15	643.64	879.48
Unit Price per Exporter: Median	10.06	10.42	11.69	12.02	11.86	12.30	15.52
Unit Price per Entrant: Median		9.46	10.90	11.54	10.75	11.77	14.14
Unit Price per Exiter: Median		9.15	9.36	10.19	11.04	11.03	11.28
Export Value per Entrant: Median (thousand USD)		31.94	27.80	36.94	32.34	33.53	35.51
Export Value per Exiter: Median (thousand USD)		22.26	35.00	19.67	31.51	34.43	27.70
Herfindahl-Hirschman Index	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Share of top 1% Exporters in TEV (Total Export Value)	0.17	0.20	0.21	0.23	0.23	0.23	0.23
Number of HS6 Products per Exporter: Median	2	2	2	2	2	2	2
Number of Destinations per Exporter: Median	1	1	1	1	1	1	1
Firm Entry Rate		0.35	0.32	0.42	0.35	0.37	0.35
Firm Exit Rate		0.30	0.38	0.27	0.35	0.32	0.36
Firm Survival Rate		0.43	0.56	0.47	0.50	0.44	
2-year Firm Survival Rate		0.30	0.36	0.31	0.30		
3-year Firm Survival Rate		0.21	0.27	0.22			

Table C.6: Exporter Dynamics - Bangladesh IV (World Bank Data)

Men's Woven Shirts (HS 6205) - Bangladesh							
Year	2005	2006	2007	2008	2009	2010	2011
Number of Exporters	883	973	843	896	818	910	928
Number of Entrants		384	284	375	321	399	361
Number of Exiters		294	414	322	399	307	343
Export Value per Exporter: Median (thousand USD)	90.63	87.80	92.58	108.46	84.52	96.53	126.84
Export Value per Exporter: First Quartile (thousand USD)	19.56	17.88	22.94	22.23	16.21	20.06	28.83
Export Value per Exporter: Third Quartile (thousand USD)	663.47	773.99	640.09	817.64	1,013.65	847.69	1,202.85
Unit Price per Exporter: Median	9.58	9.76	10.93	11.51	11.93	12.58	15.91
Unit Price per Entrant: Median		8.78	9.60	10.97	11.43	11.87	13.95
Unit Price per Exiter: Median		8.18	8.77	9.78	10.68	11.13	11.14
Export Value per Entrant: Median (thousand USD)		29.36	28.23	30.70	20.02	28.53	35.55
Export Value per Exiter: Median (thousand USD)		22.19	27.59	27.45	29.90	21.47	20.06
Herfindahl-Hirschman Index	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Share of top 1% Exporters in TEV (Total Export Value)	0.14	0.15	0.14	0.14	0.16	0.18	0.18
Number of HS6 Products per Exporter: Median	1	1	1	1	1	1	1
Number of Destinations per Exporter: Median	1	1	1	1	1	1	1
Firm Entry Rate		0.39	0.34	0.42	0.39	0.44	0.39
Firm Exit Rate		0.33	0.43	0.38	0.45	0.38	0.38
Firm Survival Rate		0.37	0.40	0.31	0.42	0.39	
2-year Firm Survival Rate		0.21	0.23	0.18	0.26		
3-year Firm Survival Rate		0.13	0.17	0.14			

Table C.7: Exporter Dynamics - Bangladesh V (World Bank Data)

Women's Woven Shirts and Blouses (HS 6206) - Bangladesh							
Year	2005	2006	2007	2008	2009	2010	2011
Number of Exporters	582	620	521	609	557	643	603
Number of Entrants		288	215	306	233	322	263
Number of Exiters		250	314	218	285	236	303
Export Value per Exporter: Median (thousand USD)	64.60	69.86	57.57	69.23	72.33	75.38	91.18
Export Value per Exporter: First Quartile (thousand USD)	13.79	16.90	17.51	21.46	20.97	21.26	21.22
Export Value per Exporter: Third Quartile (thousand USD)	292.66	271.66	195.73	283.62	314.20	345.00	418.16
Unit Price per Exporter: Median	11.74	12.61	13.96	14.25	14.47	14.94	19.12
Unit Price per Entrant: Median		11.77	12.53	12.66	13.51	13.22	16.84
Unit Price per Exiter: Median		10.69	11.54	12.05	13.01	13.44	13.25
Export Value per Entrant: Median (thousand USD)		32.19	26.90	32.91	30.82	36.00	34.45
Export Value per Exiter: Median (thousand USD)		23.61	28.53	23.58	32.57	31.87	37.13
Herfindahl-Hirschman Index	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Share of top 1% Exporters in TEV (Total Export Value)	0.14	0.17	0.16	0.14	0.14	0.14	0.17
Number of HS6 Products per Exporter: Median	1	1	1	1	1	1	1
Number of Destinations per Exporter: Median	1	1	1	1	1	1	1
Firm Entry Rate		0.46	0.41	0.50	0.42	0.50	0.44
Firm Exit Rate		0.43	0.51	0.42	0.47	0.42	0.47
Firm Survival Rate		0.35	0.41	0.38	0.45	0.35	
2-year Firm Survival Rate		0.18	0.24	0.19	0.27		
3-year Firm Survival Rate		0.11	0.15	0.13			

C.3 General Descriptives of the Sector

Table C.8: Major Apparel Items Exported From Bangladesh, in Millions of USD

Year	Shirts	Trousers	Jackets	T-shirts	Sweaters
1995-96	807.66	112.02	171.73	366.36	70.41
1998-99	1043.11	394.85	393.44	471.88	271.7
2001-02	871.21	636.61	412.34	546.28	517.83
2004-05	1053.34	1667.72	430.28	1349.71	893.12
2007-08	915.6	2512.74	1181.52	2765.56	1474.09
2008-09	1000.16	3007.29	1299.74	3065.86	1858.62
2009-10	993.41	3035.35	1350.43	3145.52	1795.39
2010-11	1566.42	4164.16	1887.5	4696.57	2488.19

Source: Series obtained from BGMEA Databases.

Table C.9: Top 10 knitwear Exports from Bangladesh, FY2010-2011, in Million USD

HS8 and Product Description	Mil.USD
T-shirts, singlets and other vests, knitted or crocheted, of cotton.	4,430.17
Jerseys, pullovers, cardigans, waist-coats and similar articles, knitted or crocheted, of textile materials, n.e.s.	1,551.30
Jerseys, pullovers, cardigans, waist-coats and similar articles, knitted or crocheted, of cotton.	730.50
Men's or boys' shirts, knitted or crocheted, of cotton.	633.43
T-shirts, singlets and other vests, knitted or crocheted, of textile material other than cotton.	266.41
Women's or girls' briefs and panties, knitted or crocheted, of cotton.	172.64
Jerseys, pullovers, cardigans, waist-coats and similar articles, knitted or crocheted, of man-made fibres.	152.40
Women's or girls' blouses, shirts and shirt-blouses, knitted or crocheted, of cotton.	135.51
Women's or girls' trousers, bib and brace overalls, breeches and shorts, knitted or crocheted, of cotton.	132.76
Men's or boys' trousers, bib and brace overalls, breeches and shorts, knitted or crocheted, of cotton.	127.97

Source: Series obtained from BGMEA Databases.

TABLE C.10: Top 10 woven Exports from Bangladesh, FY2010-2011, in Millions USD

Product Description	Mil.USD
Men's or boys' trousers, bib and brace overalls, breeches and shorts, not knitted or crocheted, of cotton.	3298.29
Women's or girls' trousers, bib and brace overalls, breeches and shorts, not knitted or crocheted, of cotton.	1200.25
Men's or boys' shirts, not knitted or crocheted, of cotton. and 1024.51	
Men's or boys' shirts, not knitted or crocheted, of textile materials, other than wool, fine animal hair, cotton and man-made fibres.	513.96
Men's or boys' jackets and blazers, not knitted or crocheted, of synthetic fibres.	273.62
Women's or girls' trousers, bib and brace overalls, breeches and shorts, not knitted or crocheted, of textile materials, other than wool, fine animal hair, cotton and synthetic fibres	199.57
Men's or boys' trousers, bib and brace overalls, breeches and shorts, not knitted or crocheted, of textile materials, other than wool, fine animal hair, cotton and synthetic fibres.	194.35
Women's or girls' blouses, shirts and shirt-blouses, not knitted or crocheted, of cotton.	193.61
Men's or boys' trousers, bib and brace overalls, breeches and shorts, not knitted or crocheted, of synthetic fibres.	158.04
Women's or girls' jackets and blazers, not knitted or crocheted, of synthetic fibres.	119.90

Source: Series obtained from BGMEA Databases.

C.4 Auxiliary descriptives based on our Data

For the purpose of tables C.11 and C.11 below, HHI index is generated as follows:

$$HHI_N = (HHI - \frac{1}{N})/(1 - \frac{1}{N})$$

$$HHI = \sum_{1toN} (s_i)^2$$

with s_i, the share of firm i in industry and industry in this case is the whole market (knitwear and woven). The first column is just HHI, ranging from $1/N$ to one, and the second column is HHI_N ranging from zero to one.

TABLE C.11: Herfindhal-Hirschman Index, sellers

Year	Mean		N
2005	0.00105	0.00137	3101
2006	0.00098	0.00128	3352
2007	0.00101	0.00128	3673
2008	0.00107	0.00132	4100
2009	0.00112	0.00137	3992
2010	0.00122	0.00145	4354
2011	0.00117	0.00141	4144
2012	0.01714	0.01740	3883
Total	0.00313	0.00339	30599

TABLE C.12: Herfindhal-Hirschman Index, buyers, definitions above

Year	Mean		N
2005	0.00805	0.00838	2969
2006	0.00838	0.00869	3246
2007	0.00813	0.00841	3613
2008	0.00759	0.00783	4117
2009	0.00814	0.00837	4230
2010	0.00843	0.00865	4631
2011	0.00865	0.00890	3929
2012	0.01105	0.01134	3468
Total	0.00853	0.00879	30203

TABLE C.13: Proportion of Exports under the *Order System*

Buyer	**Proportion**
ASDA	1.00000
CAND	0.99901
CARREFOUR	0.99969
GAP	0.99989
HANDM	0.99847
KMART	0.99998
LEVIS	0.99959
NEXT	0.99979
PRIMARK	0.99969
TESCO	0.99995
VANHEUSEN	1.00000
VF	0.99989
WALMART	0.99995

Table C.14: Summary Statistics at the buyer-quarter level ALL BUYERS

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	90.66	639.4	0.01	82144.38	38451
Volumes in 10,000 kg per b, q - all products	6.60	28.73	0	1006.35	38451
Unit Values in USD per b, q - all products, w.a.	16.99	123.16	0.13	13521.43	38451
Simultaneous active orders per b, q	4.69	11.73	1	412	34912
Simultaneous allocation of orders per b, q	3.23	6.78	1	218	24193
Count of products per b, q	2.56	2.56	1	26	38451
Count of trade partners per b, q	2.77	4.08	1	68	37888

Table C.15: Summary Statistics at the buyer-quarter level ASDA

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	1642.93	1482.87	561.92	9200.74	31
Volumes in 10,000 kg per b, q - all products	103.97	31.16	39.18	156.36	31
Unit Values in USD per b, q - all products, w.a.	15.62	12.7	10.07	83.19	31
Simultaneous active orders per b, q	45	8.52	30	61	30
Simultaneous allocation of orders per b, q	27.93	10.71	16	55	14
Count of products per b, q	13.71	2.98	7	19	31
Count of trade partners per b, q	14.48	2.61	10	20	31

Table C.16: Summary Statistics at the buyer-quarter level CAND

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	3270.12	2407.56	617.13	11229.83	31
Volumes in 10,000 kg per b, q - all products	205.17	99.06	48.16	395.44	31
Unit Values in USD per b, q - all products, w.a.	14.66	3.84	9.99	29.39	31
Simultaneous active orders per b, q	81.77	31.55	35	152	31
Simultaneous allocation of orders per b, q	51.46	19.02	19	83	13
Count of products per b, q	15.45	4.46	6	22	31
Count of trade partners per b, q	30.23	11.99	12	50	31

Table C.17: Summary Statistics at the buyer-quarter level CARREFOUR

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	1262.56	650.42	444.96	2851.84	31
Volumes in 10,000 kg per b, q - all products	110.63	48.04	28.83	209.06	31
Unit Values in USD per b, q - all products, w.a.	11.68	4.12	8.6	29.91	31
Simultaneous active orders per b, q	50.39	15.24	23	77	31
Simultaneous allocation of orders per b, q	39.06	15.73	7	65	17
Count of products per b, q	14.39	3.26	8	21	31
Count of trade partners per b, q	21.1	5.19	10	36	30

Table C.18: Summary Statistics at the buyer-quarter level GAP

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	5287.77	6249.04	1603.66	37993.44	31
Volumes in 10,000 kg per b, q - all products	255.39	92.18	101.2	438.94	31
Unit Values in USD per b, q - all products, w.a.	19.94	17.15	13.72	111.13	31
Simultaneous active orders per b, q	96.81	40.3	43	183	31
Simultaneous allocation of orders per b, q	52.33	18.32	31	93	15
Count of products per b, q	14.42	2.41	11	20	31
Count of trade partners per b, q	19.84	3.45	13	26	31

Table C.19: Summary Statistics at the buyer-quarter level HANDM

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	10123.07	14138.39	1858.14	82144.38	31
Volumes in 10,000 kg per b, q - all products	452.81	229.26	136.38	1006.35	31
Unit Values in USD per b, q - all products, w.a.	19.46	15.02	13.62	99.55	31
Simultaneous active orders per b, q	216.83	87.81	84	412	30
Simultaneous allocation of orders per b, q	132	41.87	68	218	18
Count of products per b, q	20.52	2.92	16	26	31
Count of trade partners per b, q	47.68	8.84	33	68	31

TABLE C.20: Summary Statistics at the buyer-quarter level KMART

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	3715.22	3427.36	2364.15	21833.41	31
Volumes in 10,000 kg per b, q - all products	266.42	39.81	210.15	361.75	31
Unit Values in USD per b, q - all products, w.a.	14.2	14.19	9.42	89.95	31
Simultaneous active orders per b, q	121	14.69	88	153	31
Simultaneous allocation of orders per b, q	77.27	13.44	60	119	22
Count of products per b, q	18.48	3.15	13	26	31
Count of trade partners per b, q	45.68	5.66	37	59	31

TABLE C.21: Summary Statistics at the buyer-quarter level LEVIS

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	2262.25	1120.17	614.72	6404.69	31
Volumes in 10,000 kg per b, q - all products	180.35	59.41	61.04	304.3	31
Unit Values in USD per b, q - all products, w.a.	12.4	4.58	9.45	34.16	31
Simultaneous active orders per b, q	42.94	15.64	15	66	31
Simultaneous allocation of orders per b, q	25.18	10.89	8	44	17
Count of products per b, q	5.9	1.47	4	9	31
Count of trade partners per b, q	5.47	1.14	4	9	30

TABLE C.22: Summary Statistics at the buyer-quarter level NEXT

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	432.02	810.55	4.87	3810.81	26
Volumes in 10,000 kg per b, q - all products	19.85	25.52	0.31	79.76	26
Unit Values in USD per b, q - all products, w.a.	15.51	9.45	6.02	59.07	26
Simultaneous active orders per b, q	15.54	19.25	1	57	26
Simultaneous allocation of orders per b, q	10	11.75	1	40	17
Count of products per b, q	5.85	5.31	1	17	26
Count of trade partners per b, q	9.12	9.98	1	33	26

Table C.23: Summary Statistics at the buyer-quarter level PRIMARK

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	1656.87	1787.64	381.15	10630.47	31
Volumes in 10,000 kg per b, q - all products	129.25	48.06	47.03	255.39	31
Unit Values in USD per b, q - all products, w.a.	11.44	5.88	8.08	41.62	31
Simultaneous active orders per b, q	50.3	8.6	32	63	30
Simultaneous allocation of orders per b, q	25.7	8.99	17	49	10
Count of products per b, q	10.35	2.86	6	17	31
Count of trade partners per b, q	17.77	2.54	13	23	31

Table C.24: Summary Statistics at the buyer-quarter level TESCO

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	1309.02	743.75	483.46	4944.78	31
Volumes in 10,000 kg per b, q - all products	118.01	33.87	43.44	187.44	31
Unit Values in USD per b, q - all products, w.a.	11.62	7.69	7.54	51.3	31
Simultaneous active orders per b, q	40.83	8.05	24	60	30
Simultaneous allocation of orders per b, q	20.4	9.22	11	34	10
Count of products per b, q	15.19	2.87	7	19	31
Count of trade partners per b, q	18.84	4.75	12	29	31

Table C.25: Summary Statistics at the buyer-quarter level VANHEUSEN

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	3291.71	2187.71	1077.18	12371.67	31
Volumes in 10,000 kg per b, q - all products	223.95	92.76	82.36	415.43	31
Unit Values in USD per b, q - all products, w.a.	14.06	4.03	11.17	32.86	31
Simultaneous active orders per b, q	87.5	23.48	52	134	28
Simultaneous allocation of orders per b, q	58.8	10.49	45	80	20
Count of products per b, q	9.94	2.97	4	15	31
Count of trade partners per b, q	26.19	7.38	15	40	31

Table C.26: Summary Statistics at the buyer-quarter level VF

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	4140.55	2197.34	1534.39	13525.7	31
Volumes in 10,000 kg per b, q - all products	340.82	119.32	128.6	561.93	31
Unit Values in USD per b, q - all products, w.a.	12.06	3.62	9.39	30.4	31
Simultaneous active orders per b, q	77.90	15.25	52	107	30
Simultaneous allocation of orders per b, q	41.82	11.03	24	73	22
Count of products per b, q	12.45	2.13	9	19	31
Count of trade partners per b, q	16.84	4.32	11	25	31

Table C.27: Summary Statistics at the buyer-quarter level WALMART

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 10,000 USD per b, q - all products	4337.01	1171.04	2220.57	7044.51	31
Volumes in 10,000 kg per b, q - all products	389.69	125.69	168.81	668.66	31
Unit Values in USD per b, q - all products, w.a.	11.6	3.1	8.85	26.22	31
Simultaneous active orders per b, q	80.77	23.12	42	124	31
Simultaneous allocation of orders per b, q	60.93	19.24	33	88	15
Count of products per b, q	18.23	3.15	13	25	31
Count of trade partners per b, q	39.35	10.26	24	60	31

Table C.28: Summary Statistics at the order level ALL BUYERS

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	347.26	2073.42	0.11	603394.75	100383
Volumes in 1000 kg per order - all products	25.28	191.41	0	58525.73	100383
Unit Values in USD per order - all products, w.a.	18.74	128.4	0.1	19018.05	100383
Quarterly average volume per order, 1000 kg	14.46	23.33	0	1887.93	100383
Duration of order in quarters	1.5	0.78	1	31	100383
Count of Different products in order, HS6	1.49	0.93	1	47	100383
Count of Different products in order, HS4	1.23	0.48	1	4	100383
Price of Importer fabric in order, USD, w.a.	8.43	107.81	0	27533.17	65517

Table C.29: Summary Statistics at the order level ALL NON-LARGE BUYERS

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	263.75	2167.05	0.2	603394.75	82942
Volumes in 1000 kg per order - all products	20.4	206.86	0.01	58525.73	82942
Unit Values in USD per order - all products, w.a.	16.68	50.35	0.1	5626.3	82942
Quarterly average volume per order, 1000 kg	12.08	19.14	0.01	1887.93	82942
Duration of order in quarters	1.45	0.75	1	31	82942
Count of Different products in order, HS6	1.45	0.89	1	47	82942
Count of Different products in order, HS4	1.21	0.46	1	4	82942
Price of Importer fabric in order, USD, w.a.	8.52	121.02	0	27533.17	51867

Table C.30: Summary Statistics at the order level ASDA

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	643.78	1205.21	1.38	19539.04	772
Volumes in 1000 kg per order - all products	40.28	60.58	0.05	548.13	772
Unit Values in USD per order - all products, w.a.	20.5	62.45	3.37	1475.31	772
Quarterly average volume per order, 1000 kg	19.21	21	0.05	130.33	772
Duration of order in quarters	1.75	0.89	1	6	772
Count of Different products in order, HS6	1.73	1.06	1	8	772
Count of Different products in order, HS4	1.34	0.52	1	3	772
Price of Importer fabric in order, USD, w.a.	7.32	4.99	0.76	69.64	362

Table C.31: Summary Statistics at the order level CAND

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	719.83	1277.11	0.4	19443.57	1398
Volumes in 1000 kg per order - all products	45.26	75.21	0.02	990.24	1398
Unit Values in USD per order - all products, w.a.	18.68	25.88	2.99	651.99	1398
Quarterly average volume per order, 1000 kg	22.9	29.37	0.02	411.05	1398
Duration of order in quarters	1.76	0.89	1	7	1398
Count of Different products in order, HS6	1.47	0.82	1	8	1398
Count of Different products in order, HS4	1.19	0.44	1	4	1398
Price of Importer fabric in order, USD, w.a.	9.09	4.32	1.58	58.62	926

Table C.32: Summary Statistics at the order level CARREFOUR

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	463.2	665.2	1.1	5378.87	833
Volumes in 1000 kg per order - all products	40.52	58.78	0.06	524.84	833
Unit Values in USD per order - all products, w.a.	14.47	20.82	2.74	363.08	833
Quarterly average volume per order, 1000 kg	19.99	25.18	0.06	183.8	833
Duration of order in quarters	1.79	0.79	1	6	833
Count of Different products in order, HS6	1.87	1.38	1	11	833
Count of Different products in order, HS4	1.31	0.57	1	4	833
Price of Importer fabric in order, USD, w.a.	6.46	3.46	0.33	36.85	536

Table C.33: Summary Statistics at the order level GAP

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	1080.07	2761.37	0.35	63078.57	1514
Volumes in 1000 kg per order - all products	52.3	103.77	0.01	1479.3	1514
Unit Values in USD per order - all products, w.a.	36.47	163.61	2.76	5816.36	1514
Quarterly average volume per order, 1000 kg	23.35	37.68	0.01	390.14	1514
Duration of order in quarters	1.88	0.9	1	7	1514
Count of Different products in order, HS6	1.77	1.17	1	10	1514
Count of Different products in order, HS4	1.43	0.56	1	4	1514
Price of Importer fabric in order, USD, w.a.	7.53	5.24	1.12	151.33	1318

TABLE C.34: Summary Statistics at the order level HANDM

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	802.87	1559.09	0.11	25891.76	3795
Volumes in 1000 kg per order - all products	35.61	53.26	0	856.55	3795
Unit Values in USD per order - all products, w.a.	61.18	596.93	4.8	19018.05	3795
Quarterly average volume per order, 1000 kg	19.21	23.02	0	428.27	3795
Duration of order in quarters	1.7	0.75	1	6	3795
Count of Different products in order, HS6	1.66	1.02	1	9	3795
Count of Different products in order, HS4	1.34	0.55	1	4	3795
Price of Importer fabric in order, USD, w.a.	10.15	10.72	0.16	390.66	2707

TABLE C.35: Summary Statistics at the order level KMART

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	514.47	1261.8	0.23	43354.3	2353
Volumes in 1000 kg per order - all products	35.66	52.23	0.02	651.38	2353
Unit Values in USD per order - all products, w.a.	18.2	50.21	0.98	1665.05	2353
Quarterly average volume per order, 1000 kg	21.74	25.07	0.02	250.6	2353
Duration of order in quarters	1.56	0.82	1	9	2353
Count of Different products in order, HS6	1.68	1.11	1	11	2353
Count of Different products in order, HS4	1.32	0.59	1	4	2353
Price of Importer fabric in order, USD, w.a.	6.94	3.43	0.36	85.72	2157

Table C.36: Summary Statistics at the order level LEVIS

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	905.55	1557.46	0.32	18658.07	755
Volumes in 1000 kg per order - all products	72.08	119.6	0.01	1326.5	755
Unit Values in USD per order - all products, w.a.	17.72	35.72	3.76	720.49	755
Quarterly average volume per order, 1000 kg	39.81	50.58	0.01	339.57	755
Duration of order in quarters	1.67	0.88	1	6	755
Count of Different products in order, HS6	1.31	0.68	1	6	755
Count of Different products in order, HS4	1.16	0.43	1	4	755
Price of Importer fabric in order, USD, w.a.	6.44	2.84	2.45	21.6	620

Table C.37: Summary Statistics at the order level NEXT

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	497.49	772.2	1.32	4996.66	221
Volumes in 1000 kg per order - all products	22.92	31.23	0.07	224.83	221
Unit Values in USD per order - all products, w.a.	32.96	67.17	6.02	733.58	221
Quarterly average volume per order, 1000 kg	11.71	12.52	0.07	78.07	221
Duration of order in quarters	1.72	0.88	1	5	221
Count of Different products in order, HS6	1.75	1.08	1	7	221
Count of Different products in order, HS4	1.4	0.64	1	4	221
Price of Importer fabric in order, USD, w.a.	9.16	4.15	2.22	27.78	143

Table C.38: Summary Statistics at the order level PRIMARK

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	754.26	1633.9	4.93	24872.25	669
Volumes in 1000 kg per order - all products	58.82	105.54	0.25	962.49	669
Unit Values in USD per order - all products, w.a.	14.04	14.48	3.25	208.29	669
Quarterly average volume per order, 1000 kg	22.33	32.14	0.25	481.25	669
Duration of order in quarters	2.27	1.14	1	9	669
Count of Different products in order, HS6	1.51	0.99	1	11	669
Count of Different products in order, HS4	1.18	0.44	1	4	669
Price of Importer fabric in order, USD, w.a.	7.17	3.3	1.05	21.14	574

Table C.39: Summary Statistics at the order level TESCO

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	776.35	1383.86	1.07	13199.39	516
Volumes in 1000 kg per order - all products	70.22	123.94	0.06	1361.45	516
Unit Values in USD per order - all products, w.a.	15.94	30.7	3.14	423.9	516
Quarterly average volume per order, 1000 kg	23.01	26.89	0.06	192.68	516
Duration of order in quarters	2.31	1.47	1	11	516
Count of Different products in order, HS6	2.26	1.76	1	12	516
Count of Different products in order, HS4	1.46	0.64	1	4	516
Price of Importer fabric in order, USD, w.a.	7.51	4.36	0.18	42.26	265

Table C.40: Summary Statistics at the order level VANHEUSEN

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	548.54	834.11	0.2	9447.51	1762
Volumes in 1000 kg per order - all products	37.22	56.31	0.01	798.98	1762
Unit Values in USD per order - all products, w.a.	18.21	54.36	2.24	1898.39	1762
Quarterly average volume per order, 1000 kg	23.94	25.68	0.01	257.61	1762
Duration of order in quarters	1.44	0.71	1	7	1762
Count of Different products in order, HS6	1.46	0.68	1	7	1762
Count of Different products in order, HS4	1.15	0.39	1	4	1762
Price of Importer fabric in order, USD, w.a.	9.65	29.36	2.48	1168.12	1574

Table C.41: Summary Statistics at the order level VF

Variable	Mean	Std. Dev.	Min.	Max.	N
Value in 1000 USD per order - all products	1014.55	1694.69	3.49	13204.13	1241
Volumes in 1000 kg per order - all products	83.53	143.22	0.29	1068.33	1241
Unit Values in USD per order - all products, w.a.	14.27	12.77	3.01	180.83	1241
Quarterly average volume per order, 1000 kg	39.01	54.98	0.29	472.81	1241
Duration of order in quarters	1.87	1.03	1	9	1241
Count of Different products in order, HS6	1.76	1.26	1	12	1241
Count of Different products in order, HS4	1.41	0.67	1	4	1241
Price of Importer fabric in order, USD, w.a.	7.12	5.76	0.29	123.3	1044

TABLE C.42: Summary Statistics at the order level WALMART

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Value in 1000 USD per order - all products	828.99	965.2	0.23	7735.90	1600
Volumes in 1000 kg per order - all products	74.17	86.57	0.01	727.19	1600
Unit Values in USD per order - all products, w.a.	12.3	8.01	0.16	151.3	1600
Quarterly average volume per order, 1000 kg	47.8	53.3	0.01	384.6	1600
Duration of order in quarters	1.55	0.73	1	6	1600
Count of Different products in order, HS6	1.68	1.37	1	17	1600
Count of Different products in order, HS4	1.27	0.6	1	4	1600
Price of Importer fabric in order, USD, w.a.	6.45	2.8	1	41.14	1398

TABLE C.43: Participation of largest order in (large) buyer's demand

Percentiles	
1%	0.35
5%	0.52
10%	0.62
25%	0.93
Mean	0.91
50%	1
75%	1
90%	1
95%	1
99%	1

Table C.44: Counts of players per HS6 - Selected Woven (I)

HS6	Aggregated over Quarters						
	Size HS6	Size LB	Size UDs	Count LB	Count Buyers	Count Sellers	Sellers w/UD
620311	0.01	11.95	0.86	11	124	105	96
620312	0.12	8.93	0.94	14	275	191	168
620319	0.09	12.89	0.90	17	358	336	264
620321	0.00	3.97	0.86	3	17	16	15
620322	0.01	23.57	0.86	13	123	112	103
620323	0.00	5.34	0.83	4	20	12	12
620329	0.01	4.42	0.83	9	127	112	93
620331	0.02	25.30	0.93	14	144	161	135
620332	0.53	28.99	0.95	19	1089	1115	727
620333	0.92	19.09	0.96	19	1068	753	531
620339	0.61	35.16	0.95	19	1046	977	631
620341	0.16	14.45	0.93	17	557	453	343
620343	0.97	31.55	0.94	19	1138	962	668
620411	0.02	4.53	0.91	13	165	130	113
620412	0.02	9.52	0.88	13	235	236	197
620413	0.03	28.13	0.95	9	95	92	84
620419	0.01	20.17	0.81	10	128	137	121
620421	0.00	47.22	0.87	10	56	60	55
620422	0.01	6.24	0.94	10	127	107	98
620423	0.00	7.63	0.78	6	24	24	19
620429	0.01	5.10	0.85	8	105	102	91

Columns describe: The importance of large buyers in each product category (*Size LB*); The size of the HS6 product within exports (*Size HS6*); The proportion of lines in the product category that "use the facility" (*size UDs*); The total number of large and semi-large buyers playing in the HS6 (*Count LB*); The total number of buyers (large and non-large) active in the HS6 (*Size Buyers*); The total number of sellers playing in the HS6 (*Count Sellers*); The total number of sellers that "use the facility" in the HS6 (*Sellers w/UD*).

Table C.45: Counts of players per HS6 - Selected Woven (II)

HS6	Aggregated over Quarters						
	Size HS6	Size LB	Size UDs	Count LB	Count Buyers	Count Sellers	Sellers w/UD
620431	0.02	11.95	0.88	15	208	184	156
620432	0.32	29.46	0.93	19	828	928	638
620433	0.36	15.15	0.93	19	595	414	331
620439	0.24	24.28	0.94	18	716	723	518
620441	0.00	11.96	0.55	5	62	78	62
620442	0.24	29.19	0.92	17	862	1135	715
620443	0.02	8.11	0.92	11	161	178	158
620444	0.00	25.95	0.72	7	83	76	72
620449	0.09	21.54	0.93	16	357	445	336
620451	0.00	35.26	0.84	10	57	56	53
620452	0.40	39.85	0.92	19	894	1105	735
620453	0.03	14.90	0.78	17	161	166	149
620459	0.09	37.79	0.92	16	452	510	378
620461	0.06	27.71	0.91	15	286	251	211
620462	5.90	35.76	0.96	19	2269	2227	1151
620463	0.31	19.91	0.91	18	722	613	460
620469	1.26	27.92	0.96	19	1233	1267	799
620510	0.03	22.02	0.75	15	261	234	178
620520	4.61	39.80	0.96	19	2809	2194	1068
620530	0.26	28.39	0.97	15	643	419	315
620590	3.17	29.10	0.98	19	1918	1243	748
620610	0.02	8.14	0.90	13	254	289	233
620620	0.08	29.06	0.94	17	508	514	388
620630	0.66	25.34	0.90	18	1304	1342	795
620640	0.05	34.47	0.90	17	261	253	211
620690	0.58	29.02	0.92	19	981	983	639

Columns describe: The importance of large buyers in each product category (*Size LB*); The size of the HS6 product within exports (*Size HS6*); The proportion of lines in the product category that "use the facility" (*size UDs*); The total number of large and semi-large buyers playing in the HS6 (*Count LB*); The total number of buyers (large and non-large) active in the HS6 (*Size Buyers*); The total number of sellers playing in the HS6 (*Count Sellers*); The total number of sellers that "use the facility" in the HS6 (*Sellers w/UD*).

Table C.46: Probability of Survival of Relations with large buyers, conditional on cohort

	Probability of Survival							
First Year	2005	2006	2007	2008	2009	2010	2011	2012
2005	1.00	0.69	0.52	0.46	0.39	0.36	0.30	0.28
2006		1.00	0.59	0.36	0.29	0.27	0.23	0.18
2007			1.00	0.62	0.44	0.33	0.24	0.21
2008				1.00	0.54	0.42	0.33	0.29
2009					1.00	0.51	0.36	0.34
2010						1.00	0.63	0.43
2011							1.00	0.61
2012								1.00

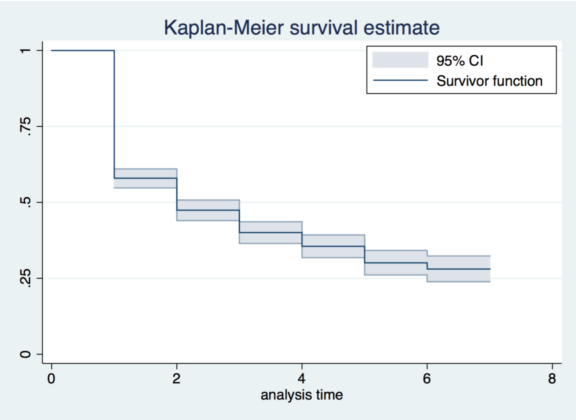


FIGURE C.16: Survival Function at the relationship level.
Analysis time is normalized so each time unit corresponds to a year of relationship between the buyer and the seller, irrespective of the calendar-time. Censoring both above and below are corrected for. Break-ups that coincide with cases in which the buyer stops purchasing the main product that she used to supply from a given seller within 6 months after the breakup are excluded.

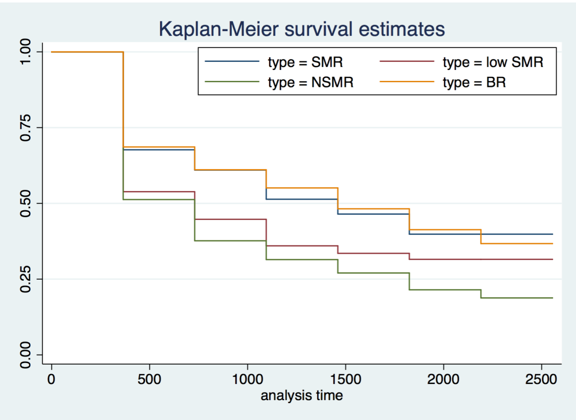


FIGURE C.17: Survival Function at the relationship level, by type of buyer.
Analysis time is normalized so each time unit corresponds to a year of relationship between the buyer and the seller, irrespective of the calendar-time. Censoring both above and below are corrected for. Break-ups that coincide with cases in which the buyer stops purchasing the main product that she used to supply from a given seller within 6 months after the breakup are excluded. *SMR* refers to specialized mass retailers and is divided into lower end retailers and higher end retailers; *NSMR* include non specialised mass retailers and are, in general, super and hypermarkets; *BR* stands for brands and include higher end brands and brands conglomerates.

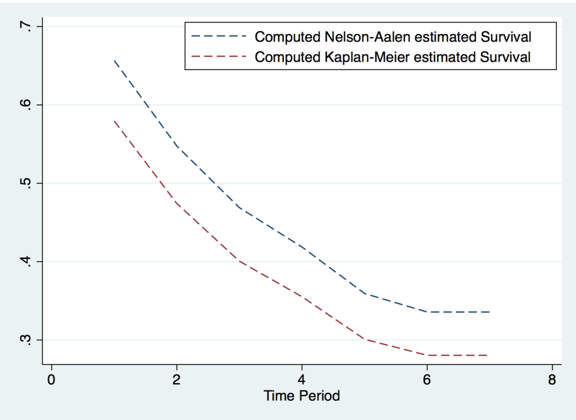


FIGURE C.18: Survival Function at the relationship level - Estimated Alternatives .

TABLE C.47: Survival Parametric Regressions - Exponential Distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Seller starts relation with another large buyer	0.188**	0.196**	0.205**	0.215***	0.222***	0.237***		0.925***	0.551***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)		(0.28)	(0.10)
Seller starts relation with (another) SMR							0.549***		
							(0.15)		
Average price, b, s in year, w.a. logs	-0.488***	-0.492***							
	(0.08)	(0.08)							
Price in the first order of relation, logs			-0.228***	-0.239***	-0.222***	-0.035	-0.222***	-0.006	0.145
			(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.20)	(0.27)
Traded volume, b, s in year, logs		-0.053***							
		(0.02)							
Volume traded in the first order of relation, logs	-0.004	0.024	0.017	0.018	0.001	0.021	0.002		
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)		
Number of quarters of active trade, b, s in year	-0.622***	-0.561***	-0.635***	-0.631***	-0.629***	-0.658***	-0.626***	-0.950***	-0.852***
	(0.05)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
lowSMR					0.352**		0.336**	0.362	
					(0.16)		(0.15)	(0.22)	
NSMR					0.311***		0.296***		
					(0.09)		(0.09)		
BR					0.141		0.126	0.043	
					(0.11)		(0.10)	(0.27)	
Fixed Effect largest product in relation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect cohort	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Fixed Effect buyer	No	No	No	No	No	Yes	No	No	No
Interaction buyer and cohort	No	No	No	No	No	Yes	No	No	No
Fixed Effect seller	No	No	No	No	No	No	No	Yes	Yes
Observations	1858	1858	1858	1858	1858	1765	1858	1015	750

Clustered Standard Errors. Key: s: seller; q: quarter; b: buyer; m: market. ** p ¡0.10, ** p ¡0.50, *** p ¡ 0.01*

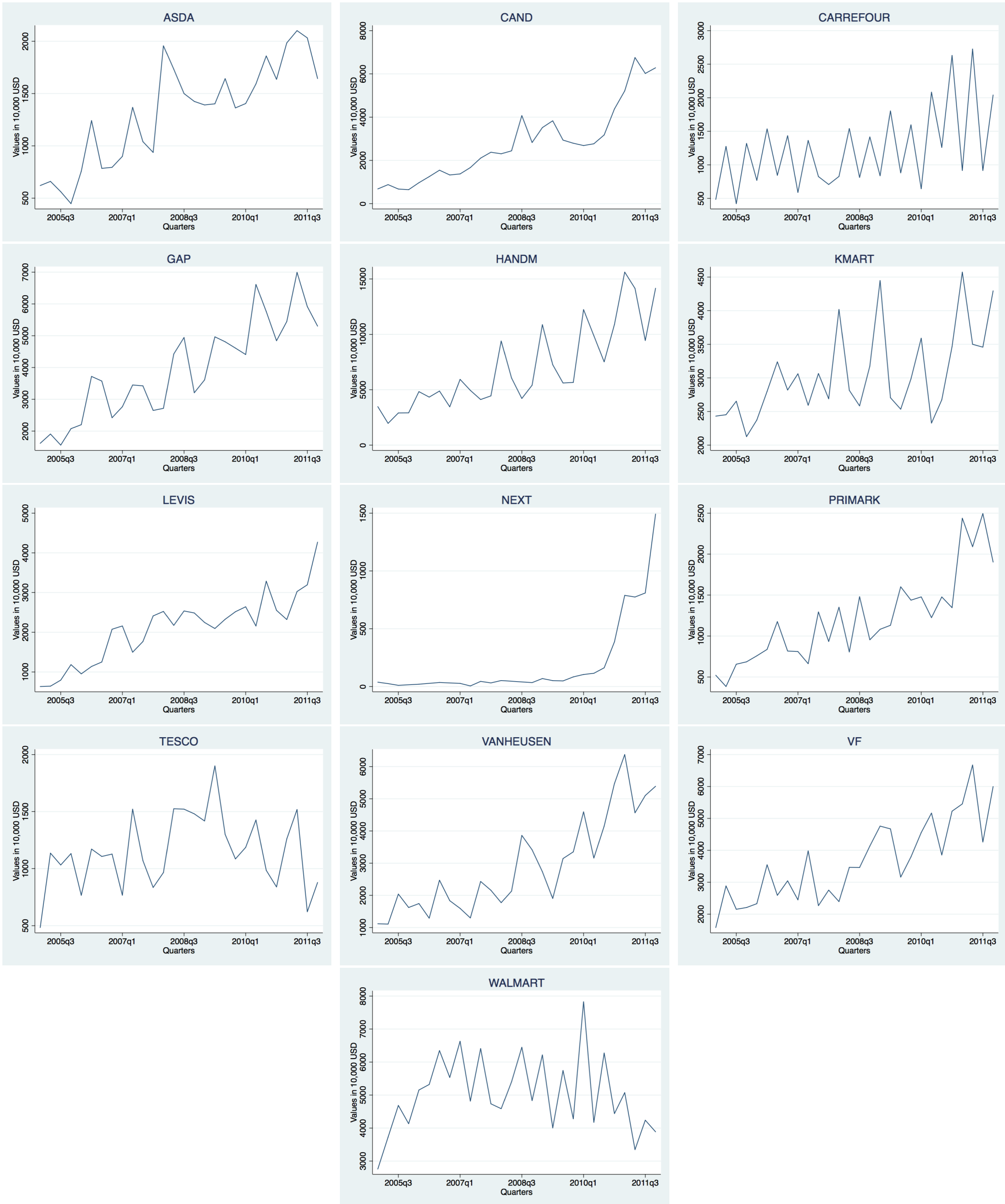


FIGURE C.19: Traded value, per buyer, by quarter, 2005q1 - 2011q4 (not deseasonalised)

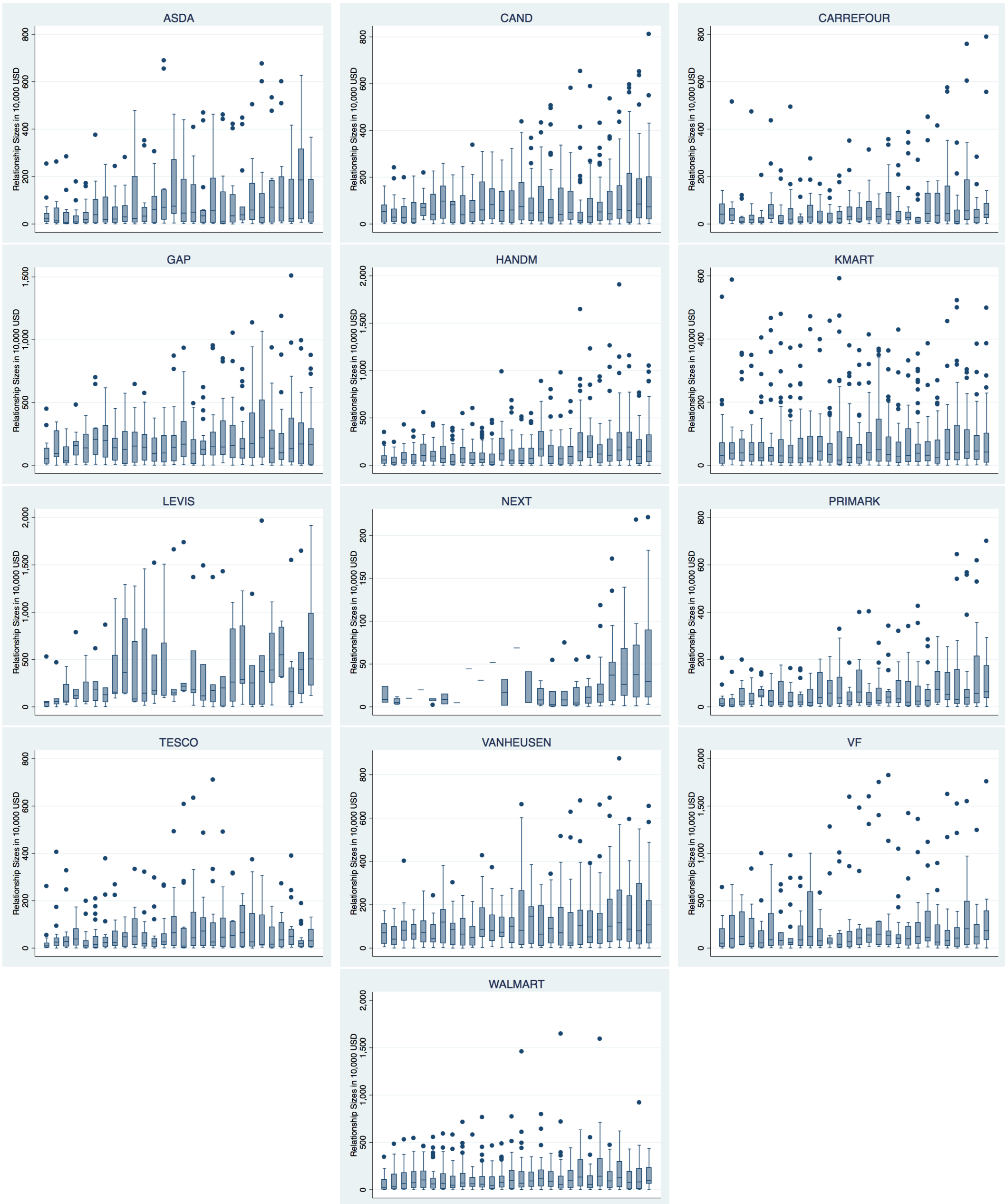


FIGURE C.20: Traded value, per buyer-seller pair, by quarter, 2005q1 - 2011q4

Table C.48: Evolution of Relations Over time - Panel A, with dummies for new comers

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.042***	0.021***	0.021***	-0.001*	0.012***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
SMR*Trend	0.036**	0.059***	-0.023***	-0.004*	0.060***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Low SMR*Trend	0.120***	0.115***	0.005	-0.006***	0.048***
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
NSMR*Trend	0.020	0.038**	-0.018***	0.001	0.029
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
BR*Trend	0.087***	0.081***	0.006	0.003	0.018
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
Squared Trend	-0.001***	-0.001***	0.000	0.000***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMR*Squared Trend	-0.000	-0.001***	0.001***	0.000	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Low SMR*Squared Trend	-0.004***	-0.004***	-0.000	0.000*	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NSMR*Squared Trend	-0.001*	-0.002***	0.001***	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BR*Squared Trend	-0.003***	-0.003***	-0.000	-0.000	-0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
New Comer*Trend	-0.056***	-0.042***	-0.014	-0.002	-0.023
	(0.02)	(0.01)	(0.01)	(0.00)	(0.02)
New Comer*Squared Trend	0.003***	0.003***	0.000	0.000	0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Relation Fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes
Constant	11.573***	9.118***	2.455***	0.875***	1.696***
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
Observations	62059	62059	62059	62059	62059
R^2	0.014	0.008	0.066	0.003	0.009

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered.

Table C.49: Evolution of Relations Over time - Panel B, with dummies for new comers

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.044***	0.052***	0.034***	0.017***	-0.364
	(0.01)	(0.01)	(0.01)	(0.00)	(0.42)
SMR*Trend	0.229***	0.042***	0.056***	-0.014***	1.681***
	(0.08)	(0.01)	(0.01)	(0.00)	(0.60)
Low SMR*Trend	0.130***	0.083***	0.094***	-0.011*	-1.766
	(0.05)	(0.02)	(0.03)	(0.01)	(2.34)
NSMR*Trend	0.063**	-0.004	0.004	-0.008*	-2.087
	(0.03)	(0.02)	(0.02)	(0.00)	(2.03)
BR*Trend	0.265***	0.048	0.055*	-0.007*	-8.100
	(0.06)	(0.03)	(0.03)	(0.00)	(5.32)
Squared Trend	-0.002***	-0.001***	-0.001***	0.000	0.017
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
SMR*Squared Trend	-0.002	-0.000	-0.001**	0.000***	-0.051***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Low SMR*Squared Trend	-0.005***	-0.003*	-0.003**	0.000***	0.125
	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)
NSMR*Squared Trend	-0.004***	-0.000	-0.001	0.000***	0.125
	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)
BR*Squared Trend	-0.010***	-0.001	-0.002	0.000**	0.489
	(0.00)	(0.00)	(0.00)	(0.00)	(0.34)
New Comer*Trend	-0.092**	-0.030	-0.027	-0.003	5.599*
	(0.04)	(0.03)	(0.02)	(0.01)	(3.16)
Now Comer*Squared Trend	0.004***	0.002***	0.002**	0.000	-0.309
	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)
Relation Fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes
Constant	1.817***	11.746***	9.889***	1.857***	17.555***
	(0.03)	(0.02)	(0.02)	(0.01)	(1.79)
Observations	62059	48826	48823	48823	62059
R^2	0.030	0.027	0.012	0.072	0.002

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered.

Table C.50: Evolution of Relations Over time All Large Buyers - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.074***	0.068***	0.006	-0.002	0.041***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Squared Trend	-0.002***	-0.002***	0.001***	0.000*	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.662***	10.153***	2.510***	0.837***	2.132***
	(0.08)	(0.08)	(0.03)	(0.01)	(0.06)
Observations	8334	8334	8334	8334	8334
R^2	0.030	0.015	0.130	0.002	0.008

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.51: Evolution of Relations Over time All Large Buyers - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.156***	0.069***	0.062***	0.008***	-0.984
	(0.04)	(0.01)	(0.01)	(0.00)	(1.47)
Squared Trend	-0.005***	-0.001**	-0.001***	0.000***	0.076
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)
Constant	2.900***	12.650***	10.814***	1.838***	8.226***
	(0.23)	(0.09)	(0.09)	(0.02)	(1.81)
Observations	8334	7579	7577	7577	8334
R^2	0.019	0.061	0.027	0.167	0.003

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.52: Evolution of Relations Over time SMR - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.095***	0.091***	0.005	-0.006**	0.064***
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Squared Trend	-0.002*	-0.003**	0.001**	0.000*	-0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.756***	10.074***	2.682***	0.842***	2.052***
	(0.07)	(0.07)	(0.02)	(0.01)	(0.09)
Observations	3153	3153	3153	3153	3153
R^2	0.058	0.028	0.159	0.014	0.019

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.53: Evolution of Relations Over time SMR - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.199	0.101***	0.096***	0.005	1.331*
	(0.09)	(0.01)	(0.01)	(0.00)	(0.43)
Squared Trend	-0.004	-0.002*	-0.002*	0.000**	-0.039*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Constant	3.044***	12.483***	10.507***	1.980***	2.559
	(0.37)	(0.07)	(0.04)	(0.02)	(4.38)
Observations	3153	2832	2830	2830	3153
R^2	0.055	0.109	0.073	0.126	0.002

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.54: Evolution of Relations Over time NSMR - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.048*	0.047*	0.001	-0.001	0.033
	(0.02)	(0.02)	(0.01)	(0.00)	(0.03)
Squared Trend	-0.001	-0.002**	0.001***	0.000	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.487***	10.100***	2.387***	0.833***	2.153***
	(0.13)	(0.13)	(0.06)	(0.01)	(0.06)
Observations	3678	3678	3678	3678	3678
R^2	0.011	0.015	0.116	0.005	0.013

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.55: Evolution of Relations Over time NSMR - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.088**	0.038	0.029	0.009	-1.196
	(0.03)	(0.03)	(0.02)	(0.01)	(1.89)
Squared Trend	-0.005***	-0.001	-0.001	0.000***	0.070
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)
Constant	2.512***	12.617***	10.900***	1.718***	9.905**
	(0.20)	(0.10)	(0.07)	(0.04)	(2.26)
Observations	3678	3313	3313	3313	3678
R^2	0.030	0.016	0.005	0.180	0.004

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.56: Evolution of Relations Over time BR - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.099***	0.081***	0.018	0.001	0.018
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Squared Trend	-0.002	-0.002*	-0.000	-0.000	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.865***	10.417***	2.448***	0.837***	2.227***
	(0.06)	(0.08)	(0.06)	(0.01)	(0.07)
Observations	1503	1503	1503	1503	1503
R^2	0.057	0.024	0.125	0.002	0.030

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.57: Evolution of Relations Over time BR - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.260**	0.085**	0.076**	0.009	-5.488
	(0.08)	(0.02)	(0.02)	(0.00)	(6.12)
Squared Trend	-0.010*	-0.001	-0.001*	0.000*	0.339
	(0.00)	(0.00)	(0.00)	(0.00)	(0.37)
Constant	3.450***	13.027***	11.183***	1.844***	16.573***
	(0.31)	(0.14)	(0.13)	(0.02)	(1.36)
Observations	1503	1434	1434	1434	1503
R^2	0.043	0.133	0.069	0.266	0.028

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.58: Evolution of Relations Over time New Comers - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.066*	0.060**	0.006	-0.004	0.022
	(0.03)	(0.02)	(0.01)	(0.00)	(0.02)
Squared Trend	-0.001	-0.001*	0.000	0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.258***	9.706***	2.552***	0.883***	1.719***
	(0.04)	(0.02)	(0.05)	(0.01)	(0.12)
Observations	2243	2243	2243	2243	2243
R^2	0.065	0.032	0.115	0.004	0.007

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.59: Evolution of Relations Over time New Comers - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.117**	0.071*	0.065*	0.006	1.097
	(0.03)	(0.03)	(0.03)	(0.00)	(0.48)
Squared Trend	-0.004**	-0.000	-0.001	0.000***	-0.037
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Constant	2.541***	12.203***	10.321***	1.887***	4.288
	(0.08)	(0.17)	(0.16)	(0.02)	(6.11)
Observations	2243	1936	1934	1934	2243
R^2	0.020	0.130	0.071	0.236	0.001

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. All regressions include buyer - seller fixed effects and control for seasonal effects.

Table C.60: Evolution of Volumes, averaging over Orders, within Relations

	(1) Average volume of allocated orders, logs	(2) Count of orders allocated to supplier
Quarters of effective interaction	0.011	0.126*
	(0.02)	(0.06)
Quarters of effective interaction, squared	-0.001	-0.003
	(0.00)	(0.00)
Relation Fixed Effects	Yes	Yes
Seasonal Effects	Yes	Yes
Year Effects	Yes	Yes
Constant	9.496***	2.954***
	(0.09)	(0.06)
Observations	6202	6202
R^2	0.032	0.014

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered. Orders are dated on their first shipment and aggregated over quarters for each cross sectional unit.

TABLE C.61: Evolution Input-Output Margin in Orders within Relations Over time - Alternative

	Margin between Price-per-kilo of garment and Price-per-kilo of fabric, logs				
	(1)	(2)	(3)	(4)	(5)
Linear Trend	0.003*	0.005**	0.002***	0.003**	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Forward Count of (oth) large buyers placing orders simultaneously in product category	0.007**	0.006**	0.009***	0.006**	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quadratic Trend		-0.000			
		(0.00)			
L.Margin			0.199***		
			(0.04)		
L2.Margin			0.114***		
			(0.01)		
L3.Margin			0.068**		
			(0.02)		
L4.Margin			0.076***		
			(0.02)		
L5.Margin			0.058***		
			(0.02)		
Volume of Order, logs				-0.082***	-0.086***
				(0.01)	(0.01)
Import Intensity					-0.000***
					(0.00)
Product Fixed Effects	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes
Buyer-Seller Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	1.707***	1.669***	0.806***	2.493***	2.539***
	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
Observations	12047	12047	5297	12047	12047
R^2	0.378	0.380	0.473	0.391	0.392

Standard errors are clustered at the relationship level. Only relationships that survive for more than a year are taken into account. Orders with *high* volumes of imported inputs are considered (see Appendix D for alternatives).

Table C.62: Evolution Price of Orders within Relations Over time - Alternative

	Average Price of Order, logs				
	(1)	(2)	(3)	(4)	(5)
Linear Trend	0.003***	0.005***	0.001***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Forward Count of (oth) large buyers placing orders simultaneously in product category	0.004*	0.004*	0.007***	0.004*	0.004**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quadratic Trend		-0.000**			
		(0.00)			
L.Average Price			0.280***		
			(0.04)		
L2.Average Price			0.160***		
			(0.03)		
L3.Average Price			0.071***		
			(0.01)		
L4.Average Price			0.082***		
			(0.01)		
L5.Average Price			0.081***		
			(0.02)		
Volume of Order, logs				-0.063***	-0.066***
				(0.00)	(0.00)
Import Intensity					-0.000***
					(0.00)
Product Fixed Effects	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes
Buyer-Seller Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	2.661***	2.623***	0.888***	3.263***	3.301***
	(0.06)	(0.06)	(0.14)	(0.05)	(0.05)
Observations	12061	12061	10311	12061	12061
R^2	0.465	0.470	0.543	0.484	0.485

Standard errors are clustered at the relationship level. Only relationships that survive for more than a year are taken into account. Orders with *high* volumes of imported inputs are considered (see Appendix D for alternatives).

Table C.63: Evolution Price of Inputs in Orders within Relations Over time - Alternative

	Average Price of Fabric in Order, logs				
	(1)	(2)	(3)	(4)	(5)
Linear Trend	0.003***	0.004***	0.002***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Forward Count of (oth) large buyers placing orders simultaneously in product category	-0.001	-0.001	0.002	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quadratic Trend		-0.000**			
		(0.00)			
L.Average Price of Fabric			0.110***		
			(0.01)		
L2.Average Price of Fabric			0.091***		
			(0.02)		
L3.Average Price of Fabric			0.082***		
			(0.01)		
L4.Average Price of Fabric			0.100***		
			(0.01)		
L5.Average Price of Fabric			0.063***		
			(0.01)		
Volume of Order, logs				-0.027***	-0.029***
				(0.00)	(0.00)
Import Intensity					-0.000*
					(0.00)
Constant	2.118***	2.092***	1.241***	2.377***	2.404***
	(0.10)	(0.10)	(0.13)	(0.10)	(0.11)
Observations	12061	12061	5784	12061	12061
R^2	0.584	0.588	0.644	0.590	0.591

Standard errors are clustered at the relationship level. Only relationships that survive for more than a year are taken into account. Orders with *high* volumes of imported inputs are considered (see Appendix D for alternatives).

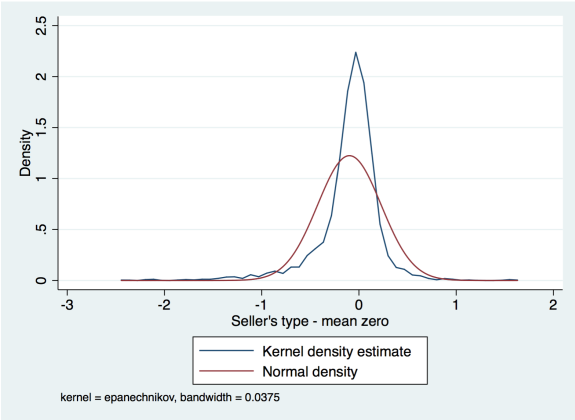


FIGURE C.21: Kernel Density Estimate: Sellers' types

TABLE C.64: Share of Demand from Large Buyers in each quintile of the distribution of sellers' types

	Large Buyer	
Quintiles	Specialized	Non-Specialized
1	0.028	0.048
2	0.056	0.061
3	0.115	0.235
4	0.296	0.290
5	0.470	0.247

Types computed excluding large buyers.

TABLE C.65: Share of the top Three Origins for each code of fabric

HS4	Bangladesh	China	Germany	Hong Kong	India	Country Name Korean Republic of	Malaysia	New Taiwan	Pakistan	Thailand	Total
5111		0.6672		0.1466				0.0874			0.3004
5208		0.5396		0.2248					0.0971		0.2871
5209		0.3850		0.2183	0.1544						0.2526
5210		0.5985		0.0830					0.0923		0.2579
5211		0.4773		0.2652					0.1299		0.2908
5212		0.5272		0.2590					0.0773		0.2878
5407		0.4855		0.0855				0.2690			0.2800
5512		0.5459		0.0774				0.2102			0.2778
5513		0.4386		0.1079					0.1164		0.2210
5514		0.5045		0.1452				0.2371			0.2956
5515		0.3677			0.2649			0.1518			0.2615
5516		0.5217						0.2265	0.0940		0.2807
5801		0.6695		0.1718					0.0986		0.3133
5802	0.8944	0.0545			0.0168						0.3219
5803		0.6605		0.0473			0.2848				0.3309
5804		0.5042		0.2951		0.0689					0.2894
5806	0.0765	0.4627		0.3383							0.2925
5809		0.5748		0.3302				0.0490			0.3180
5903	0.1617	0.5904		0.1080							0.2867
5906		0.6716		0.0940	0.0776						0.2810
5907		0.2227		0.2190						0.4933	0.3117
6001		0.4081		0.3208				0.1010			0.2766
6002		0.2755		0.4461				0.1195			0.2804
6003		0.3750		0.1907				0.3645			0.3100
6004		0.4070			0.1414	0.1232					0.2238
6005		0.2974		0.1268		0.3956					0.2733
6006		0.2124		0.2183	0.3267						0.2525
6011		1.0000									1.0000
6021									1.0000		1.0000
6022			0.7675			0.2325					0.5000
6031					0.9464					0.0536	0.5000
6039										1.0000	1.0000
6049		0.9901								0.0099	0.5000
Total	0.3775	0.4978	0.7675	0.1965	0.2755	0.2050	0.2848	0.1816	0.2132	0.3892	0.3218

For reference, see volumes and average price of each type of product in the table below:

TABLE C.66: Quantities (in millions of kg) and Average Price (in hundreds of Tk)

HS4	Volumes and Prices	
5111	10	5.8
5208	834	5.8
5209	734	4.8
5210	57	5.9
5211	87	4.5
5212	138	6.0
5407	157	8.0
5512	136	6.0
5513	165	5.8
5514	47	6.3
5515	27	5.8
5516	14	4.9
5801	21	4.9
5802	9	2.0
5803	0	6.0
5804	2	12.7
5806	8	7.5
5809	1	4.5
5903	20	7.8
5906	2	8.9
5907	0	28.1
6001	120	5.1
6002	50	5.3
6003	33	6.8
6004	2	5.9
6005	5	7.2
6006	37	5.9
6011	0	5.5
6021	0	14.2
6022	0	12.2
6031	0	0.3
6039	0	1.4
6049	0	116.2
Total	82	10.2

C.5 A general characterisation: A note on the dynamics of relations

On average, each quarter, buyers (of all sizes) receive shipments fulfilling 4 to 5 different orders, involving -less than- 3 different suppliers. Pooling all product categories together, large buyers, in turn, hold an average of 64 orders per quarter, with the top specialised mass retailers (H&M, GAP) allocating up to 100 new orders per (active) quarter. Over all the product categories, these buyers deal with up to almost 50 suppliers at a time (with an average of 20), with the higher end brands (Levis, Next, VF) showing a lower number of sellers per quarter, averaging between 5 and 16.

Both for large and non-large buyers, orders tend to be limited to one or two products under the HS6 classification. On top of the higher number of orders placed by large buyers, their orders are on average of bigger size than those placed by smaller players: while the average size of the orders placed by non-large buyers is of 20,000 kg. of garment, this ranges from 1.5 to more than 4 times that figure for large buyers. Most orders are fulfilled in shipments that span for more than one quarter, with averages per buyer ranging from 1.5 (slightly longer than the 1.45 duration of the orders for non-large importers) to 2.3 quarters (see tables C.14 to C.42).

While the comparison between large and non-large buyers regarding the volumes of their orders gives a very clear picture, the weighted unit values (or *prices*) of these orders show large variations across buyers. The non-specialised mass retailers (in general, super and hypermarkets like Carrefour, Walmart, Tesco) have orders whose unit value is on average close to that of the non-large buyers, or even below that. At the other end, specialised retailers (H&M, Gap, Next) show average prices that double and triple that of orders placed by non-large buyers. These differences in average prices seem to have some correspondence with the price of the fabric imported by the manufacturers to serve the corresponding orders. Only a few of the large buyers (H&M, Next, Vanheusen) have an average input price above the mean of that of orders placed by non-large buyers.

In this section I offer a general characterisation of buyer - seller relations on five aspects. First, I look at the duration of relations and the probability of trade relationships with large buyers breaking up, with specific attention to survival after a first year of trade. Then, I explore the general time trends in volumes, prices, order allocation and inputs over the duration of relations with large and non-large buyers. I then turn to exploring some aspects of price setting and profitability. I finally offer some descriptives on firm-level heterogeneity to finally turn to its role in the probability of observing the formation of certain trading relations or *links*.

C.5.1 Survival and Duration of Buyer - Seller relations

The buyers we are interested in, altogether, start 1,362 *new* relations over the duration of our panel. The probability of each of these relationships surviving after their first year is around 0.57, with a gradual decay averaging a 0.37, 0.32, 0.27, 0.21 probability of the relationship remaining active in a second, third, fourth and firth years, respectively [1]. These figures are reasonably consistent with those computed at the seller-product level using the Exporters Dynamic Dataset available in the World Bank Database Library (selected indicators are included in tables C.3 to C.7 of Appendix C).

Before moving further into the characterisation of the relationships between buyers and sellers, a distinction on the nature of the traded products is in order. Our focus is on the four main broad product categories of woven garment. Each of these is divided into subcategories, according to the HS nomenclature and we work with 48 products.

[1]When looking at the survival table in C.4, note the panel starts in 2005, where we register the start of all relationships that are active in that year, as we don't have information prior to January 2005. Censoring, both above and below, will be corrected for later on in this section.

Of all of these, only 9 categories can be considered as, strictly speaking, *seasonal* with shipments taking place only in specific times of the year. These correspond to certain products made of wool, furs, animal fibres or their synthetic alternatives. In our dataset, they account for less than 0.002% of the traded values and we observe no manufacturers specialised in these products (see table F.1 in Appendix F on seasonality for details) In the same appendix, the regressions in table F.2 of the (log of) traded values over seasons show that at the level of the buyers, there is a stronger presence in the last season (October to December), which is often the case in garment, due to the higher unit price of the traded garments and the higher volumes of trade. This fact, and the specificities at the level of the buyer, also observable in figure C.19 in Appendix C, are taken care of in all the exercises in this section.

Table C.67 presents the results of the estimation of a Probit model on the probability of a relationship between a large buyer and a supplier surviving its first year [2]. Of these relations, 359 can be defined as *one off* interactions. These include relations that start in the last quarter of our panel, end in the first quarter of our panel or are restricted to trade within one quarter only and below a minimum threshold (see D for alternative thresholds). The regressions in table C.67 exclude these one-off interactions. The main estimating equation is:

$$Pr(s_{ij} = 1|X) = \Phi(\theta_i + \tau_{0;ij} + X_{ij}\beta) \tag{C.1}$$

With $\Phi(.)$ denoting the CDF of the normal distribution, i indexing buyers and j indexing sellers. The outcome variable, $s_{ij} \in \{0, 1\}$, indicates whether relation ij survived the first year of trade. Fixed effects for the buyer and the cohort of the relation are included and denoted above with θ_i and $\tau_{0;ij}$, respectively. X_{ij} contains covariates at the level of the seller or the pair, collection measures that correspond to the first year of relation or pre-relationship information. Note, however, that the data used here still has a cross-sectional structure.

Across all specifications, those relations that exhibit more intense trade, both in terms of the traded volumes (and values) and the number of products show a higher probability of survival [3]. While this is not surprising, after controlling for the volume effect, the richer specifications show a positive relation between the unit value of the traded products and the probability of survival. This holds true both for the specifications that include the

[2]Year 1 is defined as the 365 days subsequently after the date of the first shipment between the buyer and the seller.Marginal Effects (at average) of Probit MLE are presented. Standard errors are bootstrapped with clustered re-sampling. All specifications include cohort fixed effects. Key: s: seller; q: quarter; b: buyer; m: market. $*p < 0.10, **p < 0.50, ***p < 0.01$.

[3]Volumes, values and count of products are averages over the quarters in which the relationship is active.

unit value as a weighted average over all the trade between the buyer and the seller in their first year and for those that use a measure of the seller's position in the distribution of prices that the buyer pays. The variable labeled *Unit price, relative position* measures the weighted (over products) average of the normalised distance between the price the seller is paid by the buyer and the median price the buyer pays in that product category to its first-year suppliers[4]. This relation between unit values and survival is observed also in the specifications that control for the input prices.

These results show that sellers that are paid by the buyer, on average, an above-average price survive onto at least a second year of trading with the large buyer with higher probability. There are at least two stories compatible with this observation. First, the buyer can be rewarding with, ceteris paribus, higher prices those manufacturers that he values the most and then wants to keep for the following period. Second, it could be that there are intrinsic seller (or buyer-seller) heterogeneity dimensions that are captured by the price term, for instance, quality aspects that are not controlled for by the price of the fabric. Not mutually exclusive, both interpretations are plausible and posit challenges to the exogeneity assumptions in the specifications proposed in this first exploration. The sections that follow will partly address these issues but we remind the reader the exploratory nature of these estimations.

The outcome variable in all these specifications implicitly conditions on the relation having started. This probably explains why the size of the seller prior to the start of the relationship does not sort survivors and non-survivors. This fact coincides with the anecdotal evidence gathered in conversations with large buyers: the general screening of potential suppliers in aspects like productive capacity or minimum social compliance and quality standards is undertaken before the trading relation starts. It is not surprising then that after the manufacturers have passed a certain threshold capacity to be able to trade with the large buyer, this no longer affects the probability of sustaining the relationship.

The effect of trading with another large buyer on the outcome could take either sign. Sellers that have active relations with large buyers can exploit this as a signal to other potential buyers in a context in which at least part of the payoff-relevant heterogeneity of the seller is not immediately observable. Large buyers are known to exert higher monitoring efforts and quality controls, especially in social compliance matters. Then, observing a seller trading with a given large buyer can be interpreted as a guarantee that the seller has passed a certain overall quality threshold. At the same time, there

[4]Here, the positions are computed as distances to the median price and normalised by the median absolute deviation. Alternatives of this specification have used means and standard deviations, with similar results. Weights over products are given by the relative volumes of trade of each product in the first year of the buyer-seller relation.

are at least two reasons why trading with other large buyers can erode the probability of a relationship surviving. The first one became apparent to us in conversations with buyers: a seller producing for two large buyers at the same time is a potential source of leakage of designs and information. The second one is that, manufacturers being capacity constrained, in general cannot handle production of large quantities for more than one large buyer simultaneously. While sellers in general serve multiple small buyers at the same time, they tend to deal with only one large player at a time. The results in table C.67 are more compatible with the views of buyers *competing* for the manufacturer, than complementing each other via signaling mechanisms [5]. Across specifications, having traded with another large buyer reduces the probability of the relation carrying on forwards.

Finally, these preliminary regressions also show that the seller's behaviour with regards to the intensity of imported inputs does not predict significantly the probability of survival. This is consistent with the view that the decisions on the material inputs to fulfil orders placed by large buyers rest with the buyer itself[6]. Appendix D explains the administrative procedure through which the buyer specifies the characteristics of the products to buy from the seller, the type and quantity of fabric needed for manufacturing the order and, in the majority of the cases, the upstream firm that will supply the fabric.

[5]Clearly, the two mechanisms can operate at the same time, driven by different dynamics behind them.

[6]The imports intensity variable is constructed as the ratio of weight of all imported fabric over the weight of the exported garments, considering only the orders for which inputs and outputs were successfully matched and at least some fabric was imported. See D for details on the matching process.

TABLE C.67: Probability of Relation Survival beyond first year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of products in year 1	0.058***	0.050***	0.051***	0.036***	0.030***	0.028***	0.050***	0.055***	0.034***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Traded volume in year 1, logs	0.047***	0.055***		0.068***	0.060***	0.069***	0.055***	0.050***	0.056***
	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Trade a relevant product, dummy	0.076***	0.073***	0.071**	0.070**	0.098***	0.097***	0.073***	0.072***	0.101***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Trading with other large buyers, dummy	-0.198***	-0.190***	-0.189***	-0.132***	-0.119***	-0.115***	-0.190***	-0.197***	-0.124***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Largest quarterly value in past	0.023	0.016	0.017	0.021	0.015	0.014	0.016	0.020	0.020
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Previous *experience* of the seller, quarters	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unit value in year 1, w.a.		0.101***		0.117***	0.109***	0.106***	0.101***		
		(0.04)		(0.02)	(0.04)	(0.04)	(0.03)		
Traded value in year 1, logs			0.056***						
			(0.01)						
Import intensity: fabric per kilo of garment				0.004		0.004			
				(0.00)		(0.00)			
Unit value of the fabric used in year 1					0.014	0.019			0.048
					(0.03)	(0.03)			(0.03)
Unit value, relative position								0.040*	0.037*
								(0.02)	(0.02)
Cohort Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1274	1274	1274	1059	930	930	1274	1274	930

Unconditional counts of partnerships at the seller level also support the (almost) exclusive dealing picture: sellers trade with at most one large buyer at a time in the median, with the average number of large buyers per seller-season being 1.2 [7]. Further explorations show that if we consider a *simple break-up* of a buyer-seller relation to be the end of trade flows between parties, in 65% of the cases, the seller is observed starting a new relationship with another large buyer within 120 days of the break-up [8].

Beyond the first year of the relationship, survival patterns follow the general description above: The Kaplan-Meier survival estimates in graph C.16 (Appendix C) show that, after the relationship moves onto a second year, the probability of break-up decreases slowly with each year of partnership [9]. Plots of these functions dividing the relationships according to the *type* of buyer are also informative. Graph C.17 shows that the survival profile of higher end specialised mass retailers, like H&M and GAP, looks similar to what is observed in high street and higher end brands or brands conglomerates, like Vanheusen, Levis and VF. Lower end specialised retailers, such as Primark and C&A, exhibit survival patterns closer to those of non-specialised buyers (Walmart, Tesco, Asda, Carrefour). Log-rank tests support this evidence and, overall, are compatible with buyers located in the high-volume / lower-quality end of the spectrum having a higher rotation of suppliers.

Table C.68 below presents the results from fitting Cox survival models on the duration of relations. The equation for the hazard of break-up of a relation at time t, follows the proportional hazard structure:

$$h(t)_{ij} = h_0(t)exp(\delta_{k;ij} + \tau_{0;ij} + \theta_i + \psi_j + X_{ijt}\beta) \tag{C.2}$$

Again, i and j denote buyers and sellers respectively. $\delta_{k;ij}$ is a fixed effect for the main product, indexed by k, for the pair ij, $\tau_{0;ij}$ designates a fixed effect for the cohort of the relation and θ_i and ψ_j are buyer- and seller- specific dummies[10]. Clearly, each specification runs over different subsets of these fixed effects and not all of them. Finally X contains regression at the player or pair level, varying or invariant with respect to t.

[7]Time here was defined as a quarter and alternative explorations were done using 5 and 6 seasons per year, with marginal qualitative differences in the statements here.

[8]For the definition of a *simple break-up* I exclude cases in which the break up coincides with the exit of the seller from the panel. For the purpose of these counts, a relation is said to end if the relationship is not censored above -more on this in this section- and if there are no more shipments between the parties for at least 548 days (1.5 years). Alternative explorations were done with cutoffs in 1, 2 and 3 years, with no substantive differences in the results presented here.

[9]Alternative estimated Nelson-Aalen survival rates are presented in graph C.18.

[10]Note in the results table that some specifications interact these, as $\tau_{0;ij} \times \theta_i$, for example.

Parametric alternatives using an exponential distribution are included in table C.47 in appendix C and the results coincide with those presented here [11]. Censoring above and below are accounted for and the duration variable is constructed as 365 days intervals from the first occurrence of trade. Cohort years correspond to the first year of trade and failure in a relationship is identified when trade stops for more than 365 consecutive days, within the censoring-free panel [12]. Fixed effects for the main product traded in the relation, the cohort of the relation, the buyers, interactions of these and cohorts and the sellers are introduced in turn in each of the specifications below. Across all of them, the shifters for low-end specialised retailers and non-specialized mass retailers exhibit a higher hazard ratio relative to higher-end specialised firms, which in turn, don't induce a risk of failure significantly different from that of brands [13]. It can also be observed that, after controlling for the traded product, higher average prices in the relationship induce lower hazard ratios. Looking at the price in the first order the buyer places with the seller, the conditional rate of failure of the relationships decreases by 0.19 (up to 0.27, depending on the specification) with 1% increases in the price of the starting order. However, when seller fixed effects are allowed for (last two columns of the table), the rate of failure doesn't seem to change with prices.

Traded volumes, either aggregating over each year of relation or isolating the volume of the first order, doesn't seem to predict significant differences in the hazard ratios, once *seasonal* intensity is taken into account[14]. Pairs that interact over a higher number of quarters or seasons in the year, are overall less likely to see their relationship ending conditional on having survived thus far. Alternatives specifications including the number of products traded rendered the similar results, with rates of failure approximately 0.45 points lower for every additional quarter (or season) of interaction. Introducing manufacturer fixed effects brings the hazard ratio even further down, showing rates of failure that are now 0.6 lower. Survival, then, seems to be positive related to the number of quarters in the year the pair actively interacts, in other words, the *continuity* of the relationship, rather than the traded volume or the diversification over different products.

Finally, across all specifications, the seller starting a new relation with another large buyer within the year increases the hazard rate of breaking down the existing relation by at least 0.16. When attention is restricted to new relations with specialised retailers (in column (7) of table C.68), the impact is even larger reaching 0.6. The last two

[11] We omit here a discussion on the proportional hazards assumption and present in the Appendix an alternative parametric estimation with accelerated failure times. Given the descriptive nature of our exploration, further testing of these assumptions are not presented here.Weibull and loglog parametric structures were also evaluated rendering virtually the same results.

[12] All relations still active within the last 365 days before the end of our panel are considered potentially censored.

[13] Note that in the table, coefficients instead of hazard ratios are shown.

[14] This evidence difference to what is observed in Eaton et al. (2008) when studying relations between Colombian and US firms.

columns in the table show that when controlling for seller-specific shifters, the rate of failure of existing relations when starting new relations with large buyers is considerably larger. In terms of probabilities, the estimated coefficients imply that new relations induce a probability of breaking up with current buyers approximately 0.71 higher when the current buyer is specialised and 0.64 when it is a non-specialised buyer [15].

Then, these descriptive survival regressions suggest that beyond the first year of relation, the duration of buyer-seller relations is related to firm-specific characteristics, potentially reflected in the prices agreed for the orders, the *continuity* of the relation in terms of how persistent over seasons trade is and, critically, whether the seller starts trading with another large buyer.

[15]Column (8) runs over the relationships with specialized buyers of all types and column (9) includes relations with non-specialized retailers only.

TABLE C.68: Survival Cox Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Seller starts relation with another large buyer	0.153^{*}	0.154^{*}	0.141^{*}	0.159^{*}	0.152^{*}	0.162^{*}		0.931^{***}	0.606^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)		(0.26)	(0.13)
Seller starts relation with (another) SMR							0.482^{***}		
							(0.16)		
Average price, b, s in year, w.a. logs	-0.394^{***}	-0.395^{***}							
	(0.08)	(0.08)							
Price in the first order of relation, logs			-0.205^{***}	-0.224^{***}	-0.196^{***}	0.006	-0.195^{***}	0.017	0.221
			(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.20)	(0.40)
Traded volume, b, s in year, logs		-0.008							
		(0.02)							
Volume traded in the first order of relation, logs	0.012	0.016	0.030	0.031	0.022	0.042^{**}	0.023		
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)		
Number of quarters of active trade, b, s in year	-0.585^{***}	-0.576^{***}	-0.589^{***}	-0.585^{***}	-0.583^{***}	-0.622^{***}	-0.582^{***}	-0.931^{***}	-0.798^{***}
	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.09)	(0.09)
lowSMR					0.219^{**}		0.206^{**}	0.461^{**}	
					(0.10)		(0.10)	(0.22)	
NSMR					0.180^{***}		0.171^{***}		
					(0.04)		(0.04)		
BR					-0.000		-0.015	0.106	
					(0.09)		(0.09)	(0.27)	
Fixed Effect largest product in relation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect cohort	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Fixed Effect buyer	No	No	No	No	No	Yes	No	No	No
Interaction buyer and cohort	No	No	No	No	No	Yes	No	No	No
Fixed Effect seller	No	No	No	No	No	No	No	Yes	Yes
Observations	1858	1858	1858	1858	1858	1765	1858	1015	750

Clustered Standard Errors. Key: s: seller; q: quarter; b: buyer; m: market. ** p ¡0.10, ** p ¡0.50, *** p ¡ 0.01*

C.5.2 The Evolution of Buyer - Seller Relations

Over the course of the years in our panel, large buyers show, on average, a positive inter-annual growth when both traded volumes and values are examined. Growth rates are specially high for retailers that were considerably small in 2005, like Next, VF, Vanheusen and C&A. Of the more established retailers, H&M and GAP, with large starting volumes also grow fast over the course of the panel. Except from the take-off cases (Next, VF, C&A), large buyers don't seem to change significantly the overall number of suppliers they deal with. New relations balance out with end of relations giving a very mild change in the count of active suppliers per large buyer across years. A similar pattern is observed in the number of products the buyer supplies: except for the new-comers mentioned above, the buyers purchase a very similar basket of products over the period under analysis. However, with the exception of GAP, Levis and Tesco, the size of the median and average orders placed by the buyers grow over the years on average, as well as the total number of orders placed each year. This seems to describe a sourcing strategy in which, once established, large buyers don't expand the size of their base of suppliers but they grow by intensifying their trade (volumes and / or counts of orders) with existing suppliers, which might change over time.

In this context, we proceed to analyse general time trends within buyer - seller relationships. The (very) simple panel regressions below evaluate the existence of linear and quadratic time trends -t and t^2- in the evolution of relevant aspects of the relationships, allowing for buyer - seller specific intercepts (α_{ij}), seasonal corrections (ι_t) and, importantly, introducing shifters of the trends for each type of large buyer (identified by dummies d_l with $l = 1 \dots L$ and $L = 4$, making non-large buyers the base category). For different outcome variables y:

$$y_{ijt} = \alpha + \alpha_{ij} + (\gamma_a t + \gamma_b t^2) \times (1 + \sum_{l=1}^{L} \gamma_l d_l) + \iota_t + \epsilon_{ijt} \tag{C.3}$$

Table C.69 shows that, controlling for individual starting points, all relations grow over time, showing a significant upward trend in the regression of traded volumes, with a small negative significant squared effect (column (2)). Relative to relations with small buyers, those that involve specialised retailers of any type (higher end, lower end or brands) show a significantly steeper linear trend. Turning the attention to column (3), while average prices in relations with small buyers exhibit a positive trend, those with the large buyers - excluding brands - show slower or no upward trend at all when transactions are aggregated at the quarter level. Altogether, except for the relations with non specialised mass retailers, the growth in volumes seem to overcome the stagnation of prices and overall traded values grow significantly quicker over time in relations with large buyers, relative to those with smaller players (column (1)).

An alternative specification presented in table C.48 in Appendix C introduces interactions with dummies identifying 'new-comers', defined as the set of large buyers that are relatively small at the beginning of the panel and that exhibit rapid growth over the first few years. It can be observe that the relations with these large buyers show a very small positive trend and a highly significant positive quadratic trend in the series of traded volumes, showing the acceleration picture described above.

In terms of diversification patterns, the share of the main product within the relationship shows a small negative trend, while the number of traded products go up over time, for all types of buyers. This pattern is more pronounced for both types (high end and low end) of specialised mass retailers. It is known that high end brands (Levis, VF, etc.) purchase a relatively stable basket of products while non-specialised mass retailers tend to focus only in the subset of products that are relatively more commoditized, such as cotton based basic items, with no fibre mixes. This behaviour restricts the diversification patterns of these two groups of large buyers to what is observed in non-large retailers.

In Table C.70, we can see that the upward trend in volumes is accompanied by a positive slope in the count of orders placed by the buyer to the seller, for all types of buyers (column (1)). Notably, a steeper evolution is observed for all specialised large players and a sharper negative quadratic effect is also detected in all cases but that of higher end specialised mass retailers. Complementary regressions included in Appendix C show that when averages over orders placed in each quarter are taken, within the relationship the increase in volumes observed in C.69 doesn't seem to be driven by larger orders but by an increase in the number of allocated orders (C.60).

Columns (2) to (5) in this table focus on the evolution of input procurement within the relation. Focusing first on the last column, we observe that the *imports intensity*, defined here as the ratio between the volume of fabric imported to produce for the corresponding buyer and the volume of garments (output) shipped to that buyer, doesn't exhibit a significant trend for small buyers, brands and non-specialised retailers [16]. However, the imports intensity in relations with specialised mass retailers exhibit a strong upward trend. In the context of growing export volumes (column (2) table C.69 described above), this implies that the volume of imported fabric needs to be growing 'quicker' [17]. Column (3) in the table shows that the volume of imported fabric tends to increase

[16] Recall that buyer - seller intercepts are allowed for, so the lack of a trend in relations with large buyers such as brands might be explained by an already above-average imports intensity at the beginning of the relationship.

[17] Note that the observations on which C.70 runs add up to a subset of those in C.69, as (i) some relations will use no imported inputs at all and (ii) we have discarded the relations for which we didn't manage to secure a trustworthy import - output matching, as explained in Appendix D.

over time within the relationship with buyers of any size, but the time trend is steeper in relations with large specialized retailers of any type. Opposite to the evolution in volumes, the unit price of imported fabric (column (4)) present a flatter trend in the case of large buyers, and this evidence in re-visited in the next subsection [18].

[18]The regressions commented here were also run splitting the sample according to the type of buyer as shown in tables C.50 to C.59 in Appendix C. These were used to perform F-tests over the relevant coefficients, supporting the characterisation offered here.

TABLE C.69: Evolution of Relations Over time - Panel A

	(1) Traded value, logs	(2) Traded volume, logs	(3) Average price, w.a., logs	(4) Share of main product in overall trade	(5) Number of products
Trend	0.042***	0.021***	0.021***	-0.001*	0.012***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
SMR*Trend	0.036**	0.059***	-0.023***	-0.004*	0.060***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)
Low SMR*Trend	0.086***	0.089***	-0.004**	-0.007***	0.034***
	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)
NSMR*Trend	0.005	0.025	-0.020***	0.001	0.021
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
BR*Trend	0.057***	0.059***	-0.002	0.002	0.006
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Squared Trend	-0.001***	-0.001***	0.000	0.000***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMR*Squared Trend	-0.000	-0.001***	0.001***	0.000	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Low SMR*Squared Trend	-0.002	-0.002	0.000	0.000***	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NSMR*Squared Trend	-0.000	-0.001	0.001***	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BR*Squared Trend	-0.001	-0.001	-0.000	-0.000*	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Relation Fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes
Constant	11.573***	9.119***	2.455***	0.875***	1.696***
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)
Observations	62059	62059	62059	62059	62059
R^2	0.013	0.007	0.066	0.002	0.008

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered.

TABLE C.70: Evolution of Relations Over time - Panel B

	(1) Number of orders active	(2) Value of Fabric, logs	(3) Volume of Fabric, logs	(4) Average price of fabric	(5) Import Intensity
Trend	0.044***	0.052***	0.034***	0.017***	-0.363
	(0.01)	(0.01)	(0.01)	(0.00)	(0.42)
SMR*Trend	0.229***	0.042***	0.056***	-0.014***	1.681***
	(0.08)	(0.01)	(0.01)	(0.00)	(0.60)
Low SMR*Trend	0.071***	0.065**	0.077**	-0.013***	1.754**
	(0.01)	(0.03)	(0.03)	(0.00)	(0.83)
NSMR*Trend	0.043	-0.014	-0.006	-0.009*	-0.677
	(0.03)	(0.02)	(0.02)	(0.00)	(1.63)
BR*Trend	0.215***	0.033*	0.042**	-0.008**	-5.114
	(0.07)	(0.02)	(0.02)	(0.00)	(5.26)
Squared Trend	-0.002***	-0.001***	-0.001***	0.000	0.017
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
SMR*Squared Trend	-0.002	-0.000	-0.001**	0.000***	-0.050***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Low SMR*Squared Trend	-0.002***	-0.001	-0.002	0.000***	-0.069**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
NSMR*Squared Trend	-0.003***	0.000	0.000	0.000***	0.047
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
BR*Squared Trend	-0.008***	0.000	-0.000	0.000***	0.322
	(0.00)	(0.00)	(0.00)	(0.00)	(0.32)
Relation Fixed Effects	Yes	Yes	Yes	Yes	Yes
Seasonal Effects	Yes	Yes	Yes	Yes	Yes
Constant	1.817***	11.747***	9.890***	1.857***	17.501***
	(0.03)	(0.02)	(0.02)	(0.01)	(1.79)
Observations	62059	48826	48823	48823	48822
R^2	0.029	0.025	0.011	0.072	0.001

Panel regressions with fixed effects for cross sectional units (buyer-seller relation). Standard errors are clustered at the buyer level. Note that quarters of effective interaction do not coincide with calendar quarters. Only relationships that survive 4 quarters of interaction (gaps allowed for) are considered.

Appendix D

Matching Inputs and Outputs

One of the most interesting aspects of our datasets is that they allow for the matching of exports and imports at various levels of specificity. The most disaggregated one, involves matching imports and exports for a given *order*, placed by one buyer to a given manufacturer and this will be possible in a sub-sample of our data. At the other end of the spectrum, imports and exports can be matched broadly for each firm (manufacturer) in a given time period. Within these two extremes, we can perform different matching protocols.

What follows is mainly concerned with the matching procedure at the order level. I first explain the administrative device that allows for these matches and I then describe how this is expressed in our datasets. Then, I explain the procedures we followed to *clean* the relavant variables in the dataset to perform the matching. I finally compare alternative matching procedures and explain a number of refinements that we have gone through.

D.1 The Utilisation Declaration Procedure

Broadly speaking, the Ready Made Garment sector in Bangladesh relies heavily on imported inputs. This is even more the case for woven garments, where the local production of suitable fabrics and input materials is still negligible. For this reason, imported inputs for the production and exports of clothing are given preferential treatment by Customs (for details, see Thomas's section in (De Wulf and Sokol, 2005)). First, in order to help reduce the lead time in export orders in the garment sector, the clearance of textiles and other garment-relevant inputs is done within two days whenever possible, much quicker than the up to seven days for other imports. Second, manufacturers can establish bonded warehouses to facilitate the import, storage during clearance and transit of inputs, including fabrics, accessories, dyes and chemicals and yarn.

The most commonly used Customs Procedure in garment exploits what is called the Special bonded warehouse (SBW) facility. In practice, raw materials used in the production of RMG export orders are imported duty-free into SBWs, manufactured into finished articles of clothing, and exported.

In the data we obtained from the Bond Commission, we identify 5,811 Bond Licences[1], out of which almost 5,000 were active in 2012, with the rest having been suspended, canceled or closed. The universe of licences we observe are matched to 5,377 firms in our dataset, identified by BINs[2]. Of the licences that correspond to garment exporters or related importers of raw materials (more on this later), 64% are associated to SBWs, 18% to Private Bonded Warehouses (PBW), 2% to EPZ Warehousing and the remainder has no specified type, as far as we could classify. These correspond to older licences (some of which are no longer active), opened during the nineties, when the Licence Number included no code identifying the type of facility. Restricting the attention to those GBO codes that correspond to garment firms, 80% of the licences are SBWs. The vast majority of the SBWs are located in the Chittagong port area, with Dhaka being the second location in importance.

In simple terms, to take advantage of the tax exemption, a firm holding a Bond Licence, after receiving an order from a buyer, opens - if needed - a Letter of Credit in the manufacturer's bank (in occasions, this will be a back-to-back Letter of Credit). To produce for that order, the manufacturer is allowed to import raw materials duty-free for a value equivalent to up-to 75% of the value of the export order. In every import shipment under the umbrella of that order, the manufacturers declares a Utilization Declaration (UD) number, issued by the Bangladesh Garments Manufacturing and Export Association (BGMEA) or corresponding alternative association and the specifics of the import transaction are recorded in the bonder's and customs' *passbooks*, which act as a record of stock going into the SBW. This procedure takes place with every import shipment within the relevant order or UD. Likewise, every export shipment that corresponds to the UD, is recorded under the same UD number for clearance. The customs modernization project that started in 1999, introduced an electronic tracking system of the goods in the SBWs facility, enabling both bonders and Custom Stations to retrieve accounts on flows into any individual SBW to reconcile this with physical movements of inputs and outputs, without relying on passbooks.

[1] This document is required for the access to any type of Bonded warehouse. Moreover, each licence includes the specific codes the licence holder is allowed to import and any additions follow a specific request of permission from Bond, with support from the relevant Industry Association.

[2] The almost 500 licenses we don't match with our data can correspond to EPZ firms in other sectors or textile companies that are not exporting garment. A quick exploration of the firms names, show textiles and packaging as the most common activities of the licence holders that are not in garment.

The evaluation of the suitability of the exception is almost entirely down to the industry Association, after the Duty Drawback Authority outsourced this activity. The key role of the Association is to control that the input-output coefficients implied in the proposed Utilisation Declaration is adequate, to restrict abuses to the system. It is expected that the ASYCUDA++ system internalises in the future the UD formula for calculating the coefficients of utilization of raw materials to finished articles, to automatically track the goods flow. At the moment, the ex-post control is done in the clearance stage.

The UD document contains all the information needed for calculating the input-output coefficients and for their evaluation in the Association. The main body of the UD specifies the characteristics of each item in the order (size, style, etc.), the destination country, the quantity and the unit value. For each of these items, there is a chart that specifies the inputs (fabrics and accessories) required, whether imported or domestically supplied, including its value and characteristics and, in most of the cases, the firms that are going to supply these inputs. Based on this, the BGMEA experts assess the output-input consistency and approve the order or recommends amendments. The second part of the UD contains information on the LCs and local inputs. First the number and date of the Export LC opened against the corresponding order is shown, with its value and the estimated shipping date. Second, the LCs for imported inputs are described, showing the country, LC number, date and value, per LC. Third the LC for local inputs are listed. The third part of the UD contains a detailed description of the items in the order: description of the garment, quantity, measures per size for the whole size chart. Then, a table presented all the required inputs, shows the imported inputs separated from domestically sourced items and each of these are divided into fabrics and yarn on one hand and accessories on the other. Within each of these categories (for example, imported fabrics or domestic yarn), per item in the order of the UD, there is a description of the input required, the total quantity and the input requirement per unit-piece of garment in that item (fabrics only), together with the supplier's name, address and country (if appropriate).

UDs constitute the main document that allows firms to claim for the duty exception, and are issued at the discretion of the Association. BGMEA gathers the majority of the garment exporters. Exporters of knitwear only, can alternatively obtain their UDs through the Bangladesh Knitwear Manufacturers and Exporters Association (BKMEA). Garment manufacturers based in Export Processing Zones follow a similar procedure under the EPZ Association (BEPZA), to access EPZ Warehouses. A manufacturer can submit a UD application only if it is a regular member of the Association and non-members need to register before applying. BGMEA members pay a fee of 450 to 650 BDTk (slow or fast track) per application they submit. This Association receives around

500 UDs a day (plus 300 amendments), and takes from hours to a couple of days to have the process finished.

To the UD application, the manufacturer needs to attach a number of documents collected in a Scrutiny Sheet. This contains the date of submission and corresponding port, the name of the firm, the BIcode (unique identifier for the firm given by BGMEA or BKMEA), the Bond licence number, the associated UD number and the name of the buyer that placed the original order. The UD number will in general follow the structure BGMEA / DHK / YY / XXXX / ZZ. BGMEA corresponds to the Association issuing the UD. Alternatively, it can read BKMEA. The second part, DHK, corresponds to Dhaka, and can alternatively be CH for the Chittagong Office. YY corresponds to the year of submission (and must coincide with the date of submission in the header). XXXX is the BIcode that BGMEA assigns. BKMEA has its own system of codes and the two institutions have completely separated numbering systems. For this reason, the same XXXX in two UDs can be identifying two different firms, one registered with BKMEA and the other one with BGMEA. ZZ corresponds to the number of UDs the firm has placed in year YY. The first UD that the firm submits in the year will take ZZ = 01, the next one will be 02, and so on.

Given the above, a given UD number to be quoted in imports and exports under an order uniquely identifies all the transactions associated to that specific order. Then, all the export shipments and imports of inputs that correspond to an order placed from a buyer to a manufacturer are (in principle) recorded in the corresponding Customs Station with its UD number and this is the administrative device that allows for matching imported inputs to outputs, at the order level.

D.2 The Records in our Dataset and the Cleaning Procedure

The UD number that would allow for the input-to-output matchings at the order level as described above, is recorded in every custom office with various levels of detail and coding problems. In general, the issuing association is not recorded and only the numeric components of the UD number are present. This was potentially problematic in two ways. First, due to the fact that BKMEA and BGMEA do not coordinate the assignment of codes to firms, the first concern was that a given code could refer to two different firms, as explained above. Second, firms in Export Processing Zones, exporting through custom stations 101/1073 (DEPZ) and 303 (CHEPZ), have their UDs issued by BEPZA. Although the BEPZA numbers have a slightly different structure from that of the UDs, coding mistakes in the Export Procedure in non-EPZ-dedicated Offices could induce incorrect extractions of the UD numbers.

Issuing institution aside, we detected a lot of variation across Custom Offices on what they record in the UD field. In many cases not all the numeric components of the UD are included. An additional complication was that the order in which these components show might differed across records, making any simple extraction routine unsuitable. Other problems we encountered were associated with relevant numbers different from the UD number, but with similar structures (like dates, Bond Licence Numbers, Export / Import Permission Numbers) being coded by mistake in the UD field. Because in theory a UD can cross over different Custom Stations, differences in data entry protocols across Offices can also induce problems in the matching. We recognise that across-offices UDs are not very common, but this was still one of the concerns when writing our matching routine.

Finally, the field recording the UD number being a very flexible string space, various sorts of data-entry typos and mistakes were found.

In this context, the first challenge to merge the datasets was to extract the components from the string that identify a UD. These are: the year in which the UD is issued, the code for the exporter given by the issuing Association and the order number. After clearing the main string from strange characters, the transactions were split into Custom Offices and Extended Procedures combinations, to identify common patterns of recording the information. In occasions, breakdowns over time (years) were also necessary. For each sub-group, the main string was split into components using the most common parsing characters ("/" or space). This gave 1 to 10 components for each string. Then according to the observed patterns, the three components of the UD number were extracted following a protocol that was in most cases specific to the year, Procedure and Custom Office combination. The code implementing these extractions on the Imports Data and the Exports Data is extense and available upon request.

The result of that initial procedure was a first version of the cleaned UD numbers. A number of robustness checks, imputations and corrections were performed both on the imports and exports sides of the data. For the purpose of the description of these steps, we focus below on the exports side, which for various reasons was more complicated than the imports side.

Of all the observations in the exports dataset from 2005 onwards ($3,059,844$), 13% contain a missing value in the field collecting the UD number. Out of the non-missing lines of the whole of the data) we managed to recover a *proper* UD number for the vast majority of the observations (86%). The cleaned UD numbers are correctly distributed over Custom Offices, with 92.7% of these falling in the non-EPZ Chittagong Offices, 7% in Dhaka under non-EPZ Procedures and the remaining lines (6 cases) found in EPZ Stations. Similarly, over Ectended Procedures, we corroborated that 97.7% of the cleaned lines fall under the code that corresponds to the use of SBW, and the rest were distributed over Procedures associated to re-exports or direct exports.

The second stage of the cleaning procedure involved the following amendments and robustness checks[3].

Items within the same transaction: Two different products within the same transaction should belong to the same UD. As items in the same transaction record are associated to one invoice (pro-forma and final) they need to correspond to the same UD. Therefore, we first explore the lines in the export dataset whose UD information is missing but that belong to a shipment where at least one item has a proper record for the UD number. There are 27,858 cases under this category. In these cases, we impute the UD number of the line with UD record to all the lines in the shipment with missing information. This is one of the imputations that was not carried out on the imports side of the data, as the unique UD per transaction does not necessarily hold.

Different UD numbers within the same transaction: Similarly, it cannot be the case that within the same transaction, two different UD numbers are quoted. We have only 52 cases in which this happens and the discrepancy between UD numbers can be in one or many of the components of the UD identifier, i.e. the exporter code, the order number or the year. Discrepancies in the exporter code are solved in the following steps. Discrepancies in the year are often due to coding errors and were manually corrected. As a general rule, we make the decision of keeping, for the whole transaction, the earliest recorded year as the year of the UD. When this is not possible, we keep the year closes to that in which the transaction takes place.

Exporter Codes for BGMEA firms: Approximately 62% of the firms for which we managed to obtain at least one 'clean' UD record are present also in our complementary BGMEA dataset. The rest of the firms with UDs could be under the BKMEA orbit or might be exporting with a BIN code different to the one used to register with the Association. In fact, the vast majority of the export trasactions that didn't produce a match with the BGMEA data are classified into HS codes that fall in knitwear categories.

We use the list of firm identifiers and BGMEA internal codes to check the exporter code component of the UD numbers. For more than 92% of the sellers present in both

[3] Again, all .do files are available upon request.

datasets, the exporter code recovered in our routine coincides with the internal code that BGMEA provided us with. This, in turn, implies that less than 9% of the transactions have an exporter code in the UD that doesn't coincide with the BGMEA internal code.

The majority of these cases were connected to data entry problems (lack of parsing characters separating the components of the UD numbers, miscoding, etc.) and they were amended appropriately. In the case of a handful of sellers, the same BIN code seems to be exporting using a firm identifier in the UD coinciding with the BGMEA code and one or more additional codes that are observed systematically. Four of these companies were found to have two different codes assigned within BGMEA, corresponding, probably to two different business units. These were left unchanged.

In all the remaining cases in which the BGMEA internal code didn't coincide with the firm identifier in the UD that were not solved as explained above, were evaluated case by case. If no data coding problems were observed, the UD number was left unchanged, despite the incongruence with the BGMEA record. The exports transactions associated to these cases were mainly in knitwear categories, suggesting that these were likely to be BKMEA firms as well. All changes were done preserving the UDs that, unchanged would generate a match on the imports dataset.

Different Exporter Codes for the same seller: As mentioned above, because a manufacturer can very often use a sister company (or a specific division within the company) to open the UD process within BGMEA, many sellers, as identified by their BIN code, can have different exporter codes in the UDs. Therefore, it is not problematic to observe the firm-specific component of the UD varying for the same seller. However, around 5% of the sellers (not only associated with BGMEA now) show multiple exporter codes in their UDs that vary in a 'suspicious' way (consecutive numbers over time, is the most common pattern or codes that seem to relate to different containers in the shipment). Those cases, are corrected using the BGMEA codes as described above when appropriate and using the codes on the import dataset, whenever possible. If none of these produce a set of UD numbers consistent for the seller, the information in the UD field is discarded.

Different buyers within the same UD: As each UD is opened against a buyer's order, theoretically it cannot be the case that a given UD has two different buyers.

There were a number of UDs under the names of more than one buyer (19% of all transactions with identified UDs). The vast majority of these, corresponded to orders in which both a retailer and a trader or a logistic company showed as the buying company.

Those cases were corrected substituting the identity of the trader for that of the retailer (for the purpose of the matching only). The main exception to this imputation was in the case where the trade shows in more than 50% of the transactions within the UD. After these corrections, almost 97% of the UDs have a unique buyer. The rest of the UDs, then involving more than one buyer were removed from the analysis (flagged as non-valid UDs), as it was hard to distinguish cases of data entry error in the name of the buyer of cases of data entry error in the UD number.

Non licensed firms: Using the Bond Licences data, we explored whether lines for which we had cleaned UDs corresponded to firms (BINs) that had a valid Bond Licence. The type of mistakes we wanted to rule out was the cleaning of UD numbers for the original string for cases in which the procedure was miss-coded and the firm was not bonded. Fortunately, we found no cases of this type.

Cases where a date is available: In occasions, the original string would include a date, that is presumably related to the date in which the UD procedure was opened or the date of approval of the last amendment. Whenever possible, the year extracted as part of the UD number was checked against the recorded date. A handful of year mis-imputations were corrected.

Two-components matchings: There were cases in which the only two components were extractable from the original string. In most of the cases, the missing component was the order number. Some of these missings were originated in cases the information was not present in the original string and some others corresponded to lines in which many of the extracted substrings could constitute the order number (often, when amendment numbers or dates were attached to the UD number). These cases were merged using only the two available components with the imports dataset to evaluate whether any of the orders on the imports side, for the same year and exporter, could inform the third component of the UD number. Where the matches were unique, this is the year and exporter on the imports side had only one order to match with on the export side, the order number was imputed if three conditions were satisfied: (i) the weight ratio of input to output was within product-specific reasonable bounds; (ii) the material of the inputs was not at odds with the output (i.e. synthetic fabric is not imported to produce pure cotton shirts) and (iii) the time window of the exports and imports fall within a quarter. In the cases where more than one match was produced and there were candidate substrings extracted from the original string on the exports side, scanning the candidate substring with the potential orders rendered a unique choice of number to impute as order.

These amendments had little impact in the overall matching but helped guarantee that there are no major omissions in the the datasets that we used for work on matched data, due to failing to march export lines[4].

Consistency at the Buyer-Seller-Product level: Due to the initial condition of the variable that records the UD number and the various cleaning routines we performed to recover the codes we need for the matching, one of our concerns was to have isolated *lines* - an item in a transaction - associated to a UD that we were not able to recover from the original variable. If that was the case, when computing statistics at the level of the order from a buyer to a seller, we would not be accounting for some of the transactions within that order.

For this reason, we explored the set of transactions for which we were not able to recover the UD number. We first assumed that whenever the original variable collecting UD numbers was missing, the transaction was not associated to any UD at all. This is consistent with what we observe in the data (missings in the relevant variable coincide with Custom Offices were no UDs are used or with -almost- one off transactions in a buyer-seller pair) and with the conversations we had with the technicians at the National Board of Revenue. Then, the lines subject to the risk we refer to above were those for which there was non-missing information in the relevant variable, but for which we still didn't manage to clean a UD number.

Aggregating the transactions at the buyer-seller-product level, we first explored the proportion of transactions that having non-missing information in the UD field didn't have a proper UD number. The ratio of transactions with uncleaned UDs to all the

[4]In the whole of the exports dataset, there were 1.2 lines that didn't produce any match via UD numbers with imports. For these lines, a two-part matching was attempted, just using coincidences in the year and firm ID components of the UD number. From this matching procedure, 65% of the unmatched lines remained unmatched, meaning that the firm ID and year combination didn't have a match on the imports. Of these unmatched lines, we found that: (i) the vast majority of the unmatched lines have either of the two components of the UD number missing, and of these, 20% fall outside of the selected product categories, another 10% corresponds to lines that either belong to unsuitable sellers as defined belong or belong to Dhaka and the rest of the unmatched UDs with at least one component missing, are 99% of the time in the group of lines in which the original string for UD extraction is fully missing or the data in it has a format that suggests a document that is NOT a UD. (ii) 13% corresponds to cases in which none of the year and ID component of the UD are missing and still, a match was not found; of these, 95.5% of the cases fall into cases of: Dhaka custom offices, UD outside the set of selected categories, seller is unsuitable, no information present in the original string or the information the string is likely correspond to a procedure different from the UD. This implied that little improvement is possible over the lines that were not matched two-piece-wise. Therefore, we focussed only on the 35% of the lines that didn't have three-piece matches but that formed at least one match in the two-piece procedure (with no missings in any of the two matching components). Out of these, 20% of the lines correspond to selected product categories (88 thousand approximately), of which only 78,317 were outside Dhaka. Out of these, 68,139 corresponded to "suitable" sellers and finally, only 46,919 were uncensored. As a result, only 3.6% of the overall unmatched exports was material we could work with to improve upon the matching.

transactions with non-missing data is zero almost everywhere for all the buyer-seller-product triplets. Less than 12% of these triplets have a non-zero ratio and the vast majority of these, have a ratio equal to 1, meaning that for that specific buyer-seller-product triplet no information (on any transaction) was recovered at all from the UD fields. These are largely explained by the firms that operate in Export Processing Zones and export through *normal* custom offices (under the EPZ procedure), and that record a BEPZA number in the UD field.

For robustness, all the ratios that were strictly greater than zero and strictly smaller than one, led to the following robustness check. For each buyer-seller pair we ordered all the exports in each product, chronologically. For every transaction with no UD we explored whether the buyer-seller pair had a valid UD featuring the same product, active in a reasonable time-window with respect to the transaction with no UD. We studied this using five different time windows: a) a fixed window of 30 days; b) a window equal to the average gap between transactions in the candidate UD; c) same as b but allowing for one standard deviation from the mean; d) a window equal to the average gap taken over all the transactions between the buyer and the seller on that product; e) same as d but allowing from one standard deviation from the mean. Although this procedure would have induced some imputations of isolated transactions into clean UDs, we decided not to perform these corrections as miss-imputation carried the potential risk of introducing noise in genuinely clean and complete orders. The 4% of the buyer-seller-products for which the ratio of uncleaned UDs to all UDs is left unchanged.

D.3 The Matching Procedure

After having performed the cleaning procedures detailed above, using the three components of the UD numbers on one and other side of the data, the matching can be performed with different levels of *conservativeness*: (i) attempting matches using every UD that was extracted and cleaned; (ii) using the UDs that fall in the 'right' Extended Procedures and Custom Offices; (iii) using the UDs that were cleaned without any 'format challenges', meaning that little or no manipulation in the order of the string and with missing components were needed [5].

[5] In practice, on the imports side, this implies imposing a cutoff on the proportion of lines that were cleaned with manipulations.

Table D.1: Performance of Different Matching Combinations

[6]	Export Side	Import Side	Number of UDs (Exports)	Number of matched UDs	%
A	(i)	(i)	256,945	131,172	51.05%
B	(ii)	(ii)	254,867	130,777	51.31%
C	(iii)	(iii)	222,366	47,506	21.36%
D	(ii)+(iii)	(ii)+(iii)	220,430	47,361	21.49%[7]
E	(ii)+(iii)	(i)	220,430	124,656	56.55%

Table D.2: Matching Performance in terms of Volume of Exports

Standard	Volume of Exports Matched[8]
A	61.5%
B	61.1%
C	16.5%
D	16.0%
E	56.2%

As a robustness check, we computed the ratio between the weight of the imported fabric and the weight of the exported garment, within the UD. Excluding the ratios that are below 0.01 and winsorizing the ratios at 3.5, the histograms of ratios for the different matching alternatives look as follows:

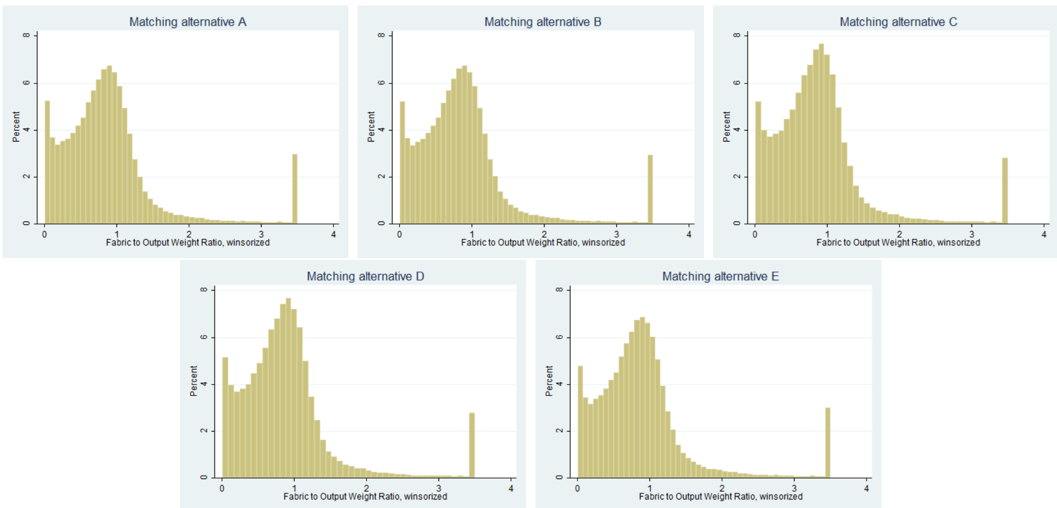


Figure D.1: Fabric to Output Ratios, Matching Comparisons

Note: UDs with ratios below 0.01 are not included. Ratios are winsorized at 3.5. A point in the histogram represents a UD.

For completeness, the table below shows the distribution of the weight of imports over input categories[9] for all the UDs that have information on the imports side and those that are matched under criterion A.

[9]See corresponding Appendix for a mapping from HS nomenclature to this classification.

TABLE D.3: Imports of different inputs, as percentages of all imports in UDs

	Percentages	
Type of Input	All UDs	Matched UDs
Fabric	61.57	63.10
Yarn	26.75	25.71
Accessories	5.94	6.05
Unclassified	4.16	3.64
Other Raw Materials	0.52	0.49
Parts	0.30	0.31
Packaging	0.24	0.23
Office Resources	0.18	0.17
Fibres	0.14	0.13
Thread	0.12	0.12
Waste	0.07	0.06
Garment	0.00	0.00
	100	100

The distribution of ratios and the *success* of the matching can be partly attributed to specificities of the production process in different product categories. The following graphs show the performance of the matching, in terms of share of the exports matched under criterion A, within each product at the 4^{th} digit of aggregation. The graphs also include the share of each product in the relevant subcategory (knitwear or woven).

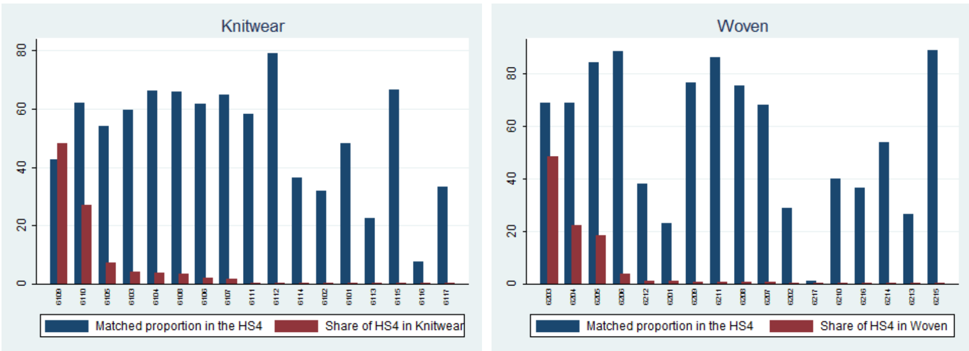


FIGURE D.2: Matching Performance over Different Product Categories

Note: Criterion A for the matching was used.

The above graphs suggest looking at the distribution of weights by product category more in detail. As orders can involve more than one product category, for the descriptives below I use only single-product UDs. Given that in terms of weight ratios and margins, the histograms above don't show significant differences across matching standards, what follows uses only alternative E. Ratio distributions correspond to fabric to output ratios and are censored at 4. If the production of a given category does not usually require imported inputs, low weight ratios (or zero) weight ratios are observed. This is likely to be the case with most of the knitwear categories were domestic provision of basic inputs (wool, cotton knitted fabrics, etc.) has developed to a reasonable standard upstream in the textile subsector.

TABLE D.4: Distribution of fabric-to-output weight ratios, per product category

Knitwear Product Categories							
HS4	N	Mean	P10	P25	P50	P75	P90
6101	20	0.66	0	0	0.81	1.1	1.27
6102	23	0.37	0	0	0	0.85	1.09
6103	829	0.65	0	0	0.65	1.04	1.33
6104	615	0.65	0	0	0.68	1.09	1.34
6105	1417	0.52	0	0	0.08	1	1.27
6106	541	0.77	0	0	0.78	1.24	1.63
6107	639	0.49	0	0	0.28	0.85	1.17
6108	1507	0.47	0	0	0.16	0.84	1.22
6109	6494	0.23	0	0	0	0.01	1.04
6110	17512	0.04	0	0	0	0	0
6111	190	0.63	0	0.09	0.6	0.99	1.18
6112	134	0.73	0	0.34	0.68	0.99	1.35
6113	9	1.01	0	0.96	1.09	1.3	1.91
6114	22	0.45	0	0	0.23	0.76	1.12
6115	100	0.05	0	0	0	0	0.13
6116	2	0.65	0.54	0.54	0.65	0.77	0.77
6117	3	0.84	0	0	0.56	1.95	1.95
Knitwear Product Categories							
HS4	N	Mean	P10	P25	P50	P75	P90
6201	241	0.74	0	0	0.51	1.11	2.02
6202	70	0.62	0	0	0.36	0.99	1.51
6203	19562	0.7	0	0.14	0.72	1.03	1.3
6204	7247	0.85	0	0.43	0.87	1.14	1.47
6205	15163	0.82	0.14	0.55	0.83	1.04	1.29
6206	2594	1.01	0.21	0.69	1	1.25	1.61
6207	320	0.86	0	0.53	0.88	1.13	1.41
6208	292	0.93	0	0.6	0.98	1.19	1.48
6209	309	0.75	0	0.47	0.81	1.04	1.2
6210	31	0.85	0	0.5	0.72	1.18	1.45
6211	378	0.79	0.15	0.5	0.76	1	1.33
6212	202	0.44	0	0	0.19	0.8	1.03
6213	1	1.22	1.22	1.22	1.22	1.22	1.22
6214	2	0.54	0	0	0.54	1.08	1.08
6215	23	0.83	0.37	0.61	0.8	1.02	1.12
6216	21	0.81	0	0	0.51	1.14	2.4

Note: Only single product UDs were used. UDs matched with criterion A.

The ratios above confirm that knitwear categories tend to rely less on imported inputs. In particular, the largest knitwear categories have median (and P75) weight ratios close to zero. Excluding the cases for which there are only a few single-item UDs (corresponding to the categories of handkerchiefs, ties, etc.), all the categories in woven seem to have relatively high median ratios. This is markedly true for the largest categories, which account for around 90% of all the woven exports (and around 48% of all garment exports). The only woven sector that is of medium size and still exhibits low/disperse ratios is 6212, which corresponds to brassieres, suspenders and other corsetieres, which use, in general, little fabric and a lot of accessories (elastics, embroidered laces, etc.).

Keeping only the single-item UDs in the woven product categories between 6203 and 6211 and re-plotting the histograms for fabric to output weight ratios gives a distribution with a much smaller spike in the lower tail:

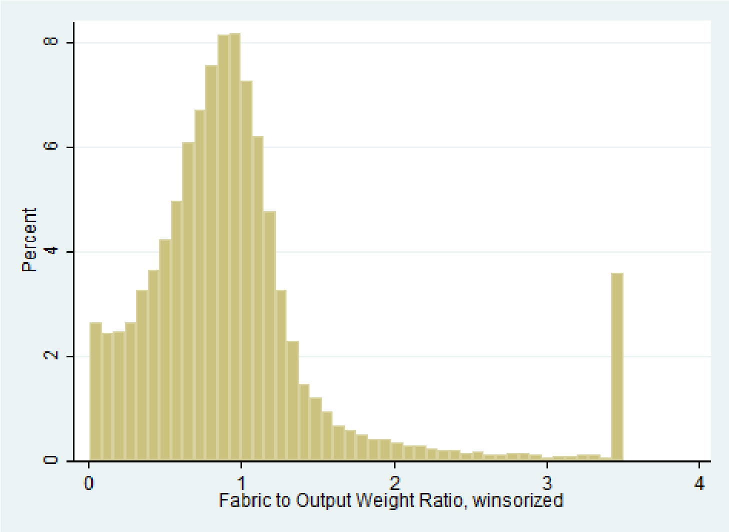


FIGURE D.3: Fabric to Output Weight Ratios, Single-Product UDs, Selected Categories

Note: UDs with ratios below 0.01 are not included. Ratios are winsorized at 3.5. A point in the histogram represents a UD. Single-Product UDs are defined as those whoe output is classified within a unique HS category, at the 4^{th} digit if aggregation. Selected Categories refer to codes 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211.

Besides the product-specificities, other potential sources for low ratios (little imports) and large margins could be connected to the characteristics of the manufacturer. It has been corroborated in the data, that there are sellers that operate in EPZs using alternative procedures, inducing outliers in the distribution of ratios for some of the criteria we are evaluating. It was also found that even outside EP Zones, there are manufacturers that never or almost never use the facility, and when they do so, the intensity of imports is still very low, inducing a ticker low tail in the distribution of ratios. Similarly, extreme ratios can be observed in UDs that are censored in our data or that are likely to be missing information due to the restrictions in our *raw* databases.

For sample selection purposes, using BIN codes as firm identifiers, these manufacturers are identified using the following cutoffs:

- EPZ manufacturers: manufacturers that have at least 75% of their exported values channeled through EPZ Custom Offices or Procedures.
- Manufacturers not using the Facility: manufacturers that have at least 85% of their exported values in transactions flagged as 'non-UD' irrespective of the Custom Office [10].

[10]Even within the relevant custom offices and procedures, there are cases in which the original string from which the UD number was extracted contains information signalling no use of the facility. These include, for instance, abbreviations referring to alternative procedures or Associations, exclusions of specific lines within larger transactions associated with UDs, etc.

- Manufacturers that don't Import: manufacturers that have at least 70% of their exporter values unmatched with any form of import.

Similar selection dummies were generated at the UD level:

- UDs in non-selected product categories: whenever less than 70% of the value of a UD falls within the selected product categories [11].
- UDs belonging to *unsuitable* sellers: whenever the UD shows a unique BIN and this corresponds to a firm that is either in the EPZ, is not using the facility or is not an importer, all of these defined as above.
- UDs in Dhaka: due to the restrictions we have in our data, we want to identify out those UDs that involve at least one transaction flowing via any of the Dhaka custom offices.
- Potentially censored UD: we consider a UD potentially censored if the first transaction associated with it occurred within the last year of our panel.
- Early UD: do to the restrictions in our data, any UD that was open before 2005 could potentially be incomplete in our data.

The interaction of these criteria produce subsamples that will exhibit different matching patterns. Different sets of selectors will be used for different purposes in this project.

D.4 Considerations around Coverage

The tables below show descriptives around coverage indicators for combinations of the filters defined in the previous section and the of the main matching criteria discussed above.

[11] Selected Categories refer to codes 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211.

Table D.5: Coverage of UDs in the exported values in Woven subsector, proportions

		Matching Criterion[12]			
	UD Filtering	Matched and Unmatched	Matched under A	Matched under B	Matched under E
1	All UDs	1.00	0.71	0.71	0.71
2	UDs with *suitable* sellers	0.98	0.69	0.69	0.69
3	UDs that are not censored	0.90	0.62	0.62	0.61
4	UDs that don't belong to Dhaka	0.57	0.52	0.52	0.52
5	UDs in the selected products	0.72	0.67	0.67	0.67
6	UDs that satisfy criteria 2 to 5	0.43	0.40	0.40	0.40

Table D.6: Coverage of UDs in the exported values in Garment sector, proportions

		Matching Criterion			
	UD Filtering	Matched and Unmatched	Matched under A	Matched under B	Matched under E
1	All UDs	1.00	0.62	0.61	0.56
2	UDs with *suitable* sellers	0.94	0.56	0.56	0.55
3	UDs that are not censored	0.89	0.53	0.53	0.49
4	UDs that don't belong to Dhaka	0.60	0.46	0.46	0.42
5	UDs in the selected products	0.36	0.34	0.34	0.33
6	UDs that satisfy criteria 2 to 5	0.22	0.20	0.20	0.20

Table D.7: Count of UDs

		Matching Criterion[13]			
	UD Filtering	Matched and Unmatched	Matched under A	Matched under B	Matched under E
1	All UDs	256,945	131,172	130,777	124,656
2	UDs with *suitable* sellers	248,150	122,377	122,096	121,215
3	UDs that are not censored	216,904	110,720	110,406	105,517
4	UDs that don't belong to Dhaka	215,525	105,260	105,069	99,560
5	UDs in the selected products	96,713	72,923	72,841	72,696
6	UDs that satisfy criteria 2 to 5	63,349	46,697	46,682	46,665

Table D.8: Count of Exporters Involved

		Matching Criterion[14]			
	UD Filtering	Matched and Unmatched	Matched under A	Matched under B	Matched under E
1	All UDs	3,315	1,572	1,568	1,513
2	UDs with *suitable* sellers	3,311	1,427	1,422	1,420
3	UDs that are not censored	3,283	1,473	1,469	1,420
4	UDs that don't belong to Dhaka	1,772	1,521	1,521	1,464
5	UDs in the selected products	1,401	1,221	1,220	1,175
6	UDs that satisfy criteria 2 to 5	1,259	1,051	1,051	1,046

TABLE D.9: Count of Buyer-Seller Relations

		Matching Criterion[15]			
	UD Filtering	Matched and Un-matched	Matched under A	Matched under B	Matched under E
1	All UDs	113,916	49,344	48,995	44,757
2	UDs with *suitable* sellers	111,914	44,107	43,809	43,247
3	UDs that are not censored	104,642	43,673	43,334	39,650
4	UDs that don't belong to Dhaka	74,112	40,760	40,714	36,891
5	UDs in the selected products	33,273	25,869	25,754	24,904
6	UDs that satisfy criteria 2 to 5	23,249	17,448	17,444	17,369

Appendix E

The Sector, Institutions and Relevant Policies

E.1 A Brief History of the Sector (before the start of our panel)

The garment sector constitutes by far the largest manufacturing activity in Bangladesh. For every year in our period of interest, garment has accounted for an average of 82% of all the exports earnings of the country. By 2013, manufacturers in the sector (domestically owned, with less that 5% of foreign ownership) employed almost 5 million people, mostly unskilled women. Overall, this accounted for more than 45% of the industrial employment in the country, whose total population sums to 156 million people. With main destinations in Europe and the United States, Bangladesh is the second largest exporter in the world -only after China- of Ready Made Garment (RMG).

The origins of the sector go back to the Pakistani ruling over Bangladesh. Most of the textile and related plants in East Pakistan were owned by investors in West Pakistan, whose industrialisation was mainly based on imports substitution. After the independence of Bangladesh in 1971, garment grew as the basis of an exports oriented industrialisation, soon overtaking jute and tea in the country's trade balance. In 1972, the Bangladesh Industrial Enterprises (Nationalization) Order (BIENO) took over most of the privately owned firms to form the state-owned Bangladesh Textile Mills Corporation (BTMC). For the subsequent years, the majority of the spinning mills were controlled by the government, although output declined slowly. After the big famine of 1974, the industrialization model started shifting from its initial state-sponsored style to a private sector led process. The first move in this direction was the New Industrial Policy (NPI), which restituted a large number of those assets (including textile mills) to their original owners.

Starting in 1974, the Multi-fiber Agreement (MFA) in the North American markets set quotas on garment trade for the industrializing Asian countries. Firms in quota-restricted countries like South Korea, started restructuring seeking for partners or green-field investments in quota-free countries. The most salient of the examples of these practices in the early development of the RMG sector in Bangladesh was the joint venture established between the South Korean giant Daewoo with the local Desh Garments Ltd., in December 1977. Only a year later 115 out of the 130 supervisors and managers in Daewoo-Desh had set up their own garment export firms or joined newly formed companies. From the early 1980s onwards, a number of economic reforms deepened the exports-oriented nature of the sector, with direct incentives to exports and the development of Export Processing Zones (EPZ) in Dhaka and Chittagong (Rashid, 2000 CITE). The early nineties continued to stimulate RMG exports (Bhattacharya and Rahman, 2000; Khundker, 2002), and the garment sector grew at a compound rate of 15% per year in this decade.

E.2 Relevant Policies in the Observed Period

The sources of information and further details for the table below are available on request. In the interest of space, the columns are omitted from the table.

Table E.1: Selected Relevant Policies in the Period of Interest

Policy Name	Authority/Institution	Start Date	End Date	Notes on Time Period	Description	Scope	Other Countries
Reformed EU Generalized System of Preferences 2012	European Union	10/25/2012	Ongoing	The regulation was signed on 25th October 2012. The scheme shall apply from 1st January 2014 up to until 31st December 2023.	(A) Grant of the three schemes (general, GSP+, and EBA), and Bangladesh is eligible for the special arrangement for EBA (Article 17); (B) Common customs tariff on all products listed in chapters 1 to 97 of the EU Combined Nomenclature, except Chapter 93, are suspended	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Quantitative Restrictions (QR)	Japan, Ministry of Economy, Trade and Industry	10/1/2012	Ongoing	The effective start date is 1st of October 2012. The notification date is 22nd January 2013. Customs Law effective on 1st August 2012.	(A) New restriction per Customs Law Unfair Competition Act of 2012; (B) Imposition of quantitative restrictions on HS 61 and 62 per WTO database	Multilateral (World)	WTO Members
Industrial Energy Efficiency Finance Program (Industrial and Infrastructure Development Finance Company)	Asian Development Bank, People's Republic of Bangladesh	12/14/2011	Ongoing	The project data sheet was updated on 8th March 2014	(A) Assistance in achieving energy efficiency in industries that may help solve the supply gap energy problem and contribute in reducing carbon emissions and air pollution and improving workers condition; (B) Provision of a program that will finance energy efficiency investments in seven industries, namely brick making, textiles, steel, cement, ceramics, chemicals, and agri-industries; (C) Improvement of competitiveness and therefore job creation and condition which will benefit workers majority of which are women; (D) Granting loan to a private sector Industrial and Development Finance Company as one of the participating financial institutions that will lend the funds to eligible energy efficiency projects in target industries mentioned in letter B	Single Country	None

Industrial Energy Efficiency Finance Program (Prime Bank Limited)	Asian Development Bank, People's Republic of Bangladesh	12/14/2011	Ongoing	The project data sheet was updated on 5th March 2013	(A) Assistance in achieving energy efficiency in industries that may help solve the supply gap energy problem and contribute in reducing carbon emissions and air pollution and improving workers condition; (B) Provision of a program that will finance energy efficiency investments in seven industries, namely brick making, textiles, steel, cement, ceramics, chemicals, and agri-industries; (C) Improvement of competitiveness and therefore job creation and condition which will benefit workers majority of which are women; (D) Granting loan to a private sector Prime Bank Limited as one of the participating financial institutions that will lend the funds to eligible energy efficiency projects in target industries mentioned in letter B	Single Country	None
Framework Agreement on Cooperation for Development between India and Bangladesh	Republic of India and People's Republic of Bangladesh	9/6/2011	Ongoing	The agreement starts on 6th September 2011 that "shall remain in force until terminated by mutual consent." See Article 12.	(A) Development of infrastructure such as transportation channels, port usage, and means of transport); (B) Grant of duty-free, quota-free access to all goods by India to Bangladesh, except for 25 items in the Sensitive List (RMG not included among the Sensitive List); (C) Before the agreement duty-free is limited to 10 million pieces of RMG per year according to an agreement made between India and Bangladesh in April 2011; (D) Duty-free for 46 RMG export items to India (see notes for the 46 RMG export items)	Bilateral	India
Technical Barriers to Trade (TBT)	Ukraine, Ministry of Industrial Policy of Ukraine, State Committee of Ukraine for Industrial Safety, Labour Protection and Mining Supervision, State Committee for Technical Regulation and Consumer Policy (DSSU)	1/1/2011	Ongoing	The proposed date of adoption and proposed date of entry into force on 1st January 2011.	(A) Imposition of technical regulations on individual means TBT on HS 6101, 6102, 6116, 6201-6204, 6210, 6211, 6216	Multilateral (World)	WTO Members

Technical Barriers to Trade (TBT)	Chinese Taipei, Ministry of Economic Affairs	8/1/2010	Ongoing	The proposed date of adoption is on 1st of August 2010. The proposed date of entry into force is on 1st January 2011.	(A) Imposition of human health TBT on HS 611120, 611130, 611190, 620920, 620930, 620990; (B) Protection of health and safety of babies from babies garments and clothing accessories; (C) Imposition of consumer protection from HS 58, 61-63, and 94 (textiles towels, sweaters garments, swimwear, underwear, hosiery, bedding); (D) Protection from hazardous substances in textile products	Multilateral (World)	WTO Members
China Duty Free Treatment	China	7/1/2010	Ongoing	China Duty Free Treatment was entered into force on 1st July 2010.	(A) Grant of preferential duty to 40 LDC beneficiaries of Duty-free Treatment; (B) Grant of duty-free quota free (DFQF) to 98.7 per cent of all imports from LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Investment Promotion and Financing Facility	The World Bank, Government of People's Republic of Bangladesh, Bangladesh Bank	5/4/2010	Ongoing	The project was approved on 4th May 2010.	(A) Expansion of long term financing for infrastructure such as: power supply, bridges, ports, container terminals, etc.; (B) Demonstration of the economic and business case for Public-Private Partnership, and building capacity of government agencies and other stakeholders on Public-Private Partnership; (C) Support Bangladesh Bank (BB) in expansion of scope funding to create jobs and remove bottlenecks in economic growth; (D) Lending of USD 47.50 Million to the project to add 178 MW of electricity generation capacity to the national grid of Dhaka Export Processing Zone and Chittagong Export Processing Zone, accounting for 5 per cent of national electricity generation capacity; (E) Provision of technical assistance to public and private financiers and entrepreneurs through PPP trainings and workshops as well as initiatives for creation of infrastructure investment funds	Single Country	None
Technical Barriers to Trade (TBT)	Republic of Korea, Korean Agency for Technology and Standards (KATS)	7/30/2009	Ongoing	The proposed date of adoption is on 1st of January 2010	(A) Imposition of human health TBT on HS 6101 and 6102 (personal flotation devices); (B) Imposition of consumer protection from textile products for infants; (C) Imposition of safety and quality labeling of textiles and leather products	Multilateral (World)	WTO Members

Technical Barriers to Trade (TBT)	United States of America, Consumer Product Safety Commission (CPSC)	5/14/2007	Ongoing	The final date for comments is on 14th May 2007. There is no proposed date of adoption nor date of entry into force.	(A) Protection of human life and health TBT on HS 61 and 62; (B) Imposition of safety on clothing textiles; (C) Protection of human life and health TBT on HS 6208	Multilateral (World)	WTO Members
Asia-Pacific Trade Agreement (formerly Bangkok Agreement)	Bangladesh; China; India; Korea, Republic of; Lao People's Democratic Republic; Sri Lanka	9/1/2006	Ongoing	This agreement was formerly known as "Bangkok Agreement," the date of entry into force of which was 17th June 1976. The entry into force of the amended agreement is on 1st September 2006.	(A) Intermediation of ESCAP, the secretariat of APTA, in the negotiation of agreements that promote inclusive growth and development; (B) Achievement of average preferential tariff on some woven garments (24.38%) and fabric HS 510810 (4.25%) as per WTO tariff database	Multilateral (Regional)	China; India; Korea, Republic of; Lao People's Democratic Republic; Sri Lanka
Kyrgyz Republic Duty Free Treatment	Kyrgyz Republic	3/29/2006	Ongoing	Initial entry into force is on 29th March 2006.	(A) Grant of preferential duty to all LDC (designated by United Nations) beneficiaries of Duty-free Treatment; (B) Grant of zero tariff rate (duty-free) on products from all LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Agreement on South Asian Free Trade Area (SAFTA)	People's Republic of Bangladesh, Kingdom of Bhutan, Republic of India, Republic of Maldives, Kingdom of Nepal, Islamic Republic of Pakistan, Democratic Socialist Republic of Sri Lanka	1/1/2006	Ongoing	It superseded SAPTA effective on 1st January 2006.	"(A) Elimination of barriers to trade; (B) Facilitation the cross-border movement of goods between the territories of the Contracting States; (C) Promotion of conditions of fair competition in the free trade area; (D) Tariff reduction by the Contracting States, non-LDCS and LDCS alike, from existing tariff rates within the time frame of 2 years from the implementation of the agreement (Article 7); (E) Special and differential treatment for LDCS, including Bangladesh (Article 11) "	Multilateral (Regional)	India, Sri Lanka, Pakistan, Bhutan, Maldives, Nepal
National Land Transport Policy	Government of People's Republic of Bangladesh	4/26/2004	Ongoing	The National Land Transport Policy was approved by the Cabinet on 26th April 2004.	(A) Government provision of safe and dependable transport service by making appropriate laws and ensuring accountability; (B) Setting environmental safety and technical standards for transport infrastructures, such as rail and land and water infrastructures; (C) Reduction of transport cost of goods towards a globally competitive trade of goods; (D) Formulation of transport system to accommodate high capacity vehicles via fly-overs, elevated expressways etc. in the greater Dhaka	Single Country	None

Chinese Taipei Duty Free Treatment	Chinese Taipei	12/17/2003	Ongoing	Chinese Taipei Duty Free Treatment was entered into force and renewed on 17th December 2003.	(A) Grant of preferential duty to all LDC (designated by United Nations) beneficiaries of Duty-free Treatment; (B) Grant of zero tariff rate (duty-free) on products from all LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Iceland Generalized System of Preferences	Iceland	1/29/2002	Ongoing	Initial entry into force is on 29th January 2002.	(A) Grant of preferential duty to developing countries and LDC beneficiaries of GPT; (B) Grant of duty-free quota-free (DFQF) or reduced tariff market access to LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Turkey Generalized System of Preferences	Turkey	1/1/2002	Ongoing	Turkey Generalized System of Preferences last date of renewal was on 1st January 2012 and has no expiration date, but Turkey performs its GSP regulations review annually.	(A) Grant of preferential duty to developing countries and LDC beneficiaries of GPT; (B) Grant of duty-free quota-free (DFQF) or reduced tariff market access to LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Republic of Korea Duty Free Treatment	Republic of Korea	1/1/2000	Ongoing	Republic of Korea Duty Free Treatment was entered into force on 1st January 2000.	(A) Grant of preferential duty to all LDC beneficiaries of Duty-free Treatment; (B) Grant of duty-free on products from all LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Special Bonded Warehouse Facilities	Customs Bond Commissionerate; Bangladesh Garments Manufacturing and Export Association	1999	Ongoing	The customs modernization project started in 1999 including the ASYCUDA++ computer system.	(A) Duty-free access to imported raw materials used for manufacturing of export products such as RMG; (B) Revenue risk mitigated through the aid of the ASYCUDA++ computer system	Single Country	None
Russian Federation Generalized System of Preferences	Russian Federation	1/1/1992	Ongoing	The GDP of Russia was renewed and expanded in 2000. The policy currently in force as of April 2011.	(A) Grant of preferential tariff treatment under the GSP scheme to 103 developing countries and 49 LDCs (including Bangladesh); (B) Grant of duty-free preferential treatment to LDCs (the list of preferential goods includes some fabrics but does not include products in HS 61 and 62)	Multilateral (World)	Beneficiary countries (particularly least developing countries)

Global System of Trade Preferences (GSTP)	Algeria; Argentina; Bangladesh; Benin; Bolivia, Plurinational State of; Brazil; Cameroon; Chile; Colombia; Cuba; Ecuador; Egypt; Ghana; Guinea; Guyana; India; Indonesia; Iran; Iraq; Korea, Democratic People's Republic of; Korea, Republic of; Libya; Malaysia; Mexico; Morocco; Mozambique; Myanmar; Nicaragua; Nigeria; Pakistan; Peru; Philippines; Singapore; Sri Lanka; Sudan; Tanzania; Thailand; The former Yugoslav Republic of Macedonia; Trinidad and Tobago; Tunisia; Venezuela, Bolivarian Republic of; Viet Nam; Zimbabwe	4/19/1989	Ongoing	The agreement was signed on 13th April 1988.	(A) Provision of duty-free access particularly processed and semi-processed goods; (B) Removal of non-tariff and para-tariff barriers; (C) Assistance to LDCs to achieve reasonable levels of sustainable exports of their products	Multilateral (World)	Developing countries
Switzerland Generalized System of Preferences	Switzerland	3/1/1972	Ongoing	Switzerland Generalized System of Preferences extended its scheme by The Swiss Parliament approval and has no expiration date yet.	(A) Grant of preferential duty to 133 developing countries and 50 LDC beneficiaries of GPT; (B) Grant of duty-free quota-free (DFQF) or reduced tariff market access to LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
New Zealand Generalized System of Preferences	New Zealand	1/1/1972	Ongoing	New Zealand Generalized System of Preferences entered into force on 1st January 1972.	(A) Grant of preferential duty to 91 developing countries and 50 LDC beneficiaries of GPT; (B) Grant of duty-free quota-free (DFQF) access to LDCs on products including 61 and 62, but will no longer be applicable once they meet a certain criteria (per capita GNI of no more than USD400)	Multilateral (World)	Beneficiary countries (mostly least developing countries)
Norway Generalized System of Preferences	Norway	10/1/1971	Ongoing	Norway Generalized System of Preferences entered into force on 1st October 1971 and has no decision for the end date yet.	(A) Grant of preferential duty to 90 countries and territories beneficiaries of GPT and of which 35 are ranked among the LDC; (B) Grant of special preferential treatment (GSP+ duty free access of goods) to all LDCs, including some products under HS 61-62	Multilateral (World)	Beneficiary countries (particularly least developing countries)

Australia Generalized System of Preferences	Australia	1/1/1966	Ongoing	The Australian System of Tariff Preferences undergone a major review in 1985.	(A) Grant of preferential duty: ASTP rate is 5% less than general tariff rate; (B) Grant of zero ASTP rate for general tariff rate that is below 5%; (C) Application of policy to all products: Bangladesh is one of the ASTP beneficiaries; (D) Grant of zero duty-free for goods under the handicraft by-law	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Japan Generalized System of Preferences	Japan	8/1/1971	3/31/2021	Japan Generalized System of Preferences runs from 1st August 1971 until 31st March 2012.	(A) Grant of preferential duty to 137 countries and 14 territories beneficiaries of GPT; (B) Grant of special preferential treatment duty and quota-free (DFQF) to all LDCs, including some products under HS 61 and 62	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Greater Dhaka Sustainable Urban Transport	Asian Development Bank, People's Republic of Bangladesh	4/17/2012	12/31/2017	The project duration is from 17th April 2012 to 31st December 2017.	(A) Provision of a better transportation for massive amount of workers in the garment factories through a sustainable bus rapid transit (BRT) corridor; (B) Provision of better and safe transportation for workers majority of which are women who commute on foot	Single Country	None
Greater Dhaka Sustainable Urban Transport Project	Asian Development Bank	4/17/2012	12/31/2017	The project duration is form 17th April 2012 to 31st December 2017.	(A) Integration of urban mobility and development of sustainable urban transport system in north of Greater Dhaka; (B) Provision of better transportation for people living and working in the area which is a garment hub with 272 factories employing about 1 million workers; (C) Provision of a better and much safer transportation for workers in the vicinity, particularly women working in the garment factories in the area (majority of the workers in the garment sector is women)	Single Country	None
Northern Areas Reduction-of-Poverty Initiative Project – Women's Economic Empowerment Project	The World Bank, Ministry of Local Government, Government of People's Republic of Bangladesh	10/27/2011	10/31/2017	The project duration is from 27th October 2011 to 31st October 2017.	(A) Provision of information, technical and life skills training, transitional housing, and other support to facilitate access to employment opportunities in the garment sector and to adjust to urban life and formal sector employment specifically for poor and vulnerable women from lagging areas of Bangladesh; (B) Raising awareness and selecting candidates in the Monga-prone districts of Northern Bangladesh; (C) Establishment of training Centre with dormitory; (D) Provision of initial training and ongoing support; (E) Supporting coordination, Monitoring and Evaluation (M and E), and program for future expansion	Single Country	None

Dhaka-Chittagong Expressway Public-Private Partnership Design Project	Asian Development Bank, People's Republic of Bangladesh	3/30/2012	3/31/2016	The project duration is form 3rd March 2012 to 31st march 2016	(A) Provision of support to the Bangladesh government to come up with design and feasibility study for the expressway connecting Dhaka and Chittagong under a public-private partnership; (B) Provision of support for the garment factories located in these metropolitan cities, Dhaka as the center and administrative capital of the country and Chittagong as the primary seaport that facilitates about 90 per cent of the foreign trade, considering that there is a lack of traffic capacity of the existing modes of transportation (e.g. 250-km highway and load restrictions in bridges)	Single Country	None
Strategic Master Plan for Chittagong Port	Asian Development Bank, People's Republic of Bangladesh	12/14/2011	12/31/2015	Strategic Master Plan for Chittagong Port is from 14th December 2011 to 31st December 2015.	(A) Preparation of a master plan for the Chittagong Port and provision of support for the integrated intermodal port development; (B) Development of port will provide better logistics and intermodal transport system and may improve regional trade	Single Country	None

Promotion of Social and Environmental Standards in Industry	European Union, German Federal Ministry for Economic Cooperation and Development, Bangladesh Ministry of Commerce	2010	2015	The overall term is from 2010 to 2015.	(A) Collaboration with ministries, authorities, business associations, local suppliers and international buyers, as well as non-governmental organizations and trade unions to improve the social and environmental standards of textiles factories; (B) Provision of training courses given to public labour inspectors and advisors to stakeholders in the garment industry; (C) Provision of courses on environmental management and water and chemicals handling to advisors who then help textiles factories to meet international standards such as registration, evaluation, authorization, and restriction of chemicals (REACH); (D) Collaboration with dyeing and washing plants as well as public and private universities and colleges to advice textile factories on environmental-friendly processing of industrial waste and disposal of chemical residues; (E) Training of energy auditors and advising textile factories about energy efficiency; (F) Supporting non-governmental organizations such as the Awaj Foundation, Dhaka and Agrajatra, Chittagong in upholding workers' rights; (G) Assisting victims of the fire and collapse accidents occurred in 2012 and 2013, respectively, by providing financial support, vocational training, and disability structures	Single Country	None
Comprehensive Disaster Management Programme (CDMP)	European Union, United Nations Development Programme, People's Republic of Bangladesh	1/1/2010	12/1/2014	The project runs from January 2010 to December 2013.	(A) Assistance in reducing the impact of natural disasters and other human-induced hazards by strengthening disaster management; (B) Provision of equipments and training for the improvement of the fire-fighting capabilities of Bangladesh Fire Service and Civil Defense Directorate	Single Country	None
Canada Generalized System of Preferences	Canada	7/1/1974	6/30/2014	General Preferential Tariff (GPT) and The Least Developed Country Tariff (LDCT) was granted an extension until 30 June 2014.	(A) Grant of preferential duty to 174 beneficiaries of GPT and 49 beneficiaries of LDCT; (B) Grant of free-duty or lower rates subject to certain conditions to items for yarns, sewing threads, fabrics, apparel and made-up textile articles imported from LDCS	Multilateral (World)	Beneficiary countries (particularly least developing countries)

Industrial Energy Efficiency Finance Program	Asian Development Bank, People's Republic of Bangladesh	12/14/2011	4/30/2013	Industrial Energy Efficiency Finance Program runs from 14th December 2011 to 30th April 2013.	(A) Assistance in achieving energy efficiency in industries that may help solve the supply gap energy problem and contribute in reducing carbon emissions and air pollution and improving workers condition; (B) Provision of a program that will finance energy efficiency investments in seven industries, namely brick making, textiles, steel, cement, ceramics, chemicals, and agri-industries; (C) Improvement of competitiveness and therefore job creation and condition which will benefit workers majority of which are women	Single Country	None
Padma Multipurpose Bridge Design Project	Asian Development Bank, People's Republic of Bangladesh	11/25/2010	8/7/2013	Padma Multipurpose Bridge Design Project (Supplementary Loan) runs from 25th November 2010 to 7th August 2013.	(A) Building of the first crossing across the Padma Bridge for road traffic; (B) Identification of cost-recovery mechanisms ensuring sustainability of the project through capacity building of institutions that manage the bridge and other related assets; (C) Provision of a better connectivity between the different zones of the country, namely northwest and southwest zones to the east zone where Dhaka and Chittagong and where many garment factories are situated	Single Country	None
Promotion of Labour Standards in RMG Sector	European Union, Deutsche Gesellschaft Fur International Zusammenarbeit	7/1/2010	6/1/2013	The project duration is 3 years from July 2010 to June 2013.	(A) Improvement of factory safety in Bangladesh; (B) Provision of support given to Ministry of Labour and Employment, BGMEA, and BKMEA in order to meet compliance audit, including fire safety; (C) Provision of training given to labour inspectors and factory compliance officers	Single Country	None
Duty Free Tariff Preference (DFTP-LDC) Scheme of India	Government of India	8/1/2008	8/1/2013	Duty Free Tariff Preference (DFTP-LDC) Scheme of India lasted for five years from August 2008.	(A) Extension of duty-free quota-free (DFQF) access to LDC members; (B) Grants of tariff preferences on the exports (including some products under HS 61 and 62) from LDC on imports to India	Multilateral Regional	Least Develop Countries
Chittagong Port Trade Facilitation Project	Asian Development Bank, People's Republic of Bangladesh	12/20/2004	8/23/2013	The project runs from 20th December 2004 to 23rd August 2013.	(A) Improvement in the efficiency of Chittagong Port in terms of building capacity for container terminal to better handle activities in the port; (B) Provision of better access to Dhaka-Chittagong corridor transportation facility: (C) Harmonization of port activities with that of Custom House Chittagong to improve traffic of international freight; (D) Provision of technical assistance and capacity building	Single Country	None

US Generalized System of Preferences	United States of America	1/1/1976	3/9/2013	The US GSP program started on 1st January 1976. The GSP eligibility of Bangladesh was suspended on 3rd September 2013 as per Presidential Proclamation 8997.	(A) Grant of preferential duty-free entry for up to 5,000 products when imported from beneficiary countries (products in HS 61 and 62 are not included in the present list); (B) Bangladesh was suspended on 3rd September 2013	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Padma Multipurpose Bridge Design Project (Supplementary Loan)	Asian Development Bank, People's Republic of Bangladesh	12/2/2009	11/6/2012	The project duration is from 2nd December 2009 to 6th November 2012.	(A) Continuation of the assistance in the design for the Padma Bridge, of the top priority projects of the Bangladesh government	Single Country	None
Priority Roads Project	Asian Development Bank, People's Republic of Bangladesh	11/23/2009	1/31/2011	Priority Roads Project was approved on 23rd November 2009 and ended on 31st January 2011.	(A) Linking of non-urban transport to major road networks, including Jamuna and Padma Bridges; (B) Strengthening of domestic trade and promotion of economic development in relatively less developed zones in the country, namely the northwest and southwest zones	Single Country	None
Greater Dhaka Sustainable Urban Transport Corridor	Asian Development Bank, People's Republic of Bangladesh	7/12/2009	1/31/2011	General Dhaka Sustainable Urban Transport Corridor was approved on 07th December 2009 and ended on 31st January 2011.	(A) Assistance in feasibility study, design, and initialization of the project with the objective of improving transportation in greater Dhaka by achieving a sustainable urban transport corridor; (B) Expectation of a better transportation for massive amount of workers in the garment factories through a sustainable bus rapid transit (BRT) corridor	Single Country	None
EU Generalized System of Preference	European Union, Delegation of the European Union to Bangladesh	1/1/2009	12/31/2011	First implemented by the EU in 1971, the present GSP scheme applies from 1st January 2009 to 31st December 2011.	(A) Reduction of 20% over the normal customs duty for textile products, duty-free for non-sensitive products; and reduction of 3.5% for sensitive products; (B) Under the "Everything but Arms," Bangladesh and all other LDCs have indefinite duty-free, quota-free access to all products	Multilateral (World)	Beneficiary countries (particularly least developing countries)
Port and Logistics Efficiency Improvement	Asian Development Bank, People's Republic of Bangladesh	11/26/2009	9/30/2010	Port and Logistics Efficiency Improvement was approved on 26th November 2009 and ended on 30th September 2010.	(A) Improvement of port operations and efficiency in intermodal transport logistics systems under the Integrated Multimodal Transport Policy	Single Country	None

Enterprise Growth and Bank Modernization	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	6/8/2004	12/31/2010	The project duration is from 8th June to 2004 to 31st December 2010.	(A) Privatization or closure of loss-making SOEs to avoid future losses and maintain employment; (B) Implementation of banking sector reform programs to achieve highly competitive private banking system through staged withdrawal of government in state-owned banks and through corporatization and divestment of government shareholding in Rupali Bank, Agrani Bank, Janata Bank, and Sonali Bank; (C) Building capacity of select public institutions and banks, including the Board of Investment, Privatization Commission, Bangladesh Export Processing Zone Authority (BEPZA), and Nationalized Commercial Banks; one indication of achieving the objectives of the project is the handing over of Chittagong Steel Mills to BEPZA, converting the former into an Export Processing Zone	Single Country	None
Dhaka Power Systems Upgrade	Asian Development Bank, People's Republic of Bangladesh	12/21/1999	4/26/2010	Dhaka Power Systems Upgrade was approved on 21st December 1999 and ended on 26th April 2010.	(A) Adoption by Dhaka Power Systems Upgrade of the paper Power Sector Reforms in Bangladesh which was formulated on 1994; (B) Improvement on management and corporate governance; (C) System expansion by providing technical assistance for planning and institutional strengthening and capital; (D) Reduce losses through improvement of transmission and distribution system in the Dhaka area	Single Country	None

Transitional Support Credit	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	6/17/2008	6/30/2009	The project runs from 17th June 2008 until 30th June 2009.	"(A) Support policy and institutional reforms of the Caretaker Government Bangladesh had from January 2007 to December 2008; (B) Mobilization of tax revenues by improving compliance and collecting past arrears rather than introducing structural reforms in the tax system; (C) Administering prices of petroleum products, urea fertilizers, and compressed natural gas in order to reduce losses in the SOEs; (D) Liberalization of trade via cutting nominal import tariff protection and simplifying tariff structure, and enhancement of export competitiveness by improving the Chittagong port and extending the Bonded Warehouse Facilities to all exports subject to minimum thresholds (World Bank 2009 Report ICR1115, p. 4); (E) Other program development objectives are improvement of public financial management, SOEs, and institutions of accountability and the business regulatory environment "	Single Country	None
Bangladesh Power Sector Development Policy Credit	The World Bank, Government of People's Republic of Bangladesh, Ministry of Power, Energy, and Mineral Resources	6/17/2008	3/31/2009	The Bangladesh Power Sector Development Policy Credit was approved on 17th June 2008 and ended on 31st March 2009.	(A) Making the processing of contracts in the power sector more competitive via efficiency and transparency; (B) Improvement of metering, billing, and collection systems of service providers leading to a reduction of commercial losses; (C) Acceleration of the development of regulatory capacity of Bangladesh Energy Regulatory Commission; (D) Increasing and improving the quality of power supply (see notes for the negative impact of power shortage to the garment sector)	Single Country	None
Chittagong Port Efficiency Improvement	Asian Development Bank, People's Republic of Bangladesh	12/20/2004	6/30/2009	The project was approved on 20th December 2004 and ended on 30th June 2009.	(A) Reorganization of Chittagong Port Authority; (B) Development of Port Master Plan and multimodal transport network for the Dhaka-Chittagong Corridor; (C) Introduction of institutional reforms particularly reforms in customs in the port that handles about 90 per cent of the foreign trade in the country	Single Country	None

Bangladesh Development Support Credits IV-Supplemental Financing II	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	1/10/2008	6/30/2008	Second Supplemental Financing to Development Support Credit IV runs from 10th January 2008 until 30th June 2008.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing satisfactory outcome with actual disbursed amount of SDR 62.9M with secondary objective of export development and competitiveness	Single Country	None
Development Support Credit IV-Supplemental Financing II	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	1/10/2008	6/30/2008	Development Support Credit IV-Supplemental Financing II was approved on 10th January 2008 and closed on 30th June 2008.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing satisfactory outcome with actual disbursed amount of SDR 62.9 M with secondary objective of export development and competitiveness	Single Country	None
Supplemental to Development Support Credit IV	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	9/27/2007	3/31/2008	Supplemental to Development Support Credit IV runs from 27th September 2007 until 31st March 2008.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing satisfactory outcome with actual disbursed amount of SDR 49M with secondary objective of export development and competitiveness	Single Country	None

Development Support Credit IV/Development Policy Lending	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	5/29/2007	6/30/2008	Development Support Credit IV runs from 29th May 2007 to 30th June 2008.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing highly satisfactory outcome with actual disbursed amount of SDR 132.2 M with secondary objective of export development and competitiveness	Single Country	None
Development of Transport Corridor for Trade Facilitation	Asian Development Bank, People's Republic of Bangladesh	7/26/2006	5/31/2007	The project was approved on 26th July 2006 and ended on 31st May 2007.	(A) Preparation of projects for ADB funding on transport links and ancillary facilities that will help facilitate cross-border movements of goods	Single Country	None
"Padma Multi-purpose Bridge Project (formerly Support for Public-Private Partnership in Padma Bridge)"	Asian Development Bank, People's Republic of Bangladesh	9/22/2005	9/30/2007	The project duration is from 2nd September 2005 to 30th September 2007.	(A) Assistance in feasibility study to confirm the economic and financial viability of the project ensuring ADB safeguard requirements such as environmental, social, and resettlement compliance	Single Country	None
Social Protection of Poor Female Workers in the Garment Sector in the Context of Changing Trade Environments	"Asian Development Bank, Ministry of Women and Children Affairs"	3/16/2004	12/31/2007	The project period is from 16th March 2004 to 31st December 2007.	(A) Improvement of job opportunities and reduction of poverty and unemployment in RMG sector for female workers specially those who are affected by the phasing out of quota under MFA; (B) Provision of training, health care, livelihood counseling and social protection	Single Country	None

Third Development Support Credit	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	12/1/2005	6/30/2006	Third Development Support Credit was approved on 1st December 2005 and closed on 30th June 2006.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing satisfactory outcome with actual disbursed amount of SDR 138.1 M with secondary objective of export development and competitiveness	Single Country	None
Social Protection for Disadvantaged Women and Children	"Asian Development Bank, People's Republic of Bangladesh, Government of Bangladesh Ministry of Women and Children Affairs"	11/2/2003	6/30/2006	The project duration is from 11th February 2003 to 30th June 2006.	(A) Provision of social protection for disadvantaged women and children; (B) Provision of assistance such as shelters for the victims of domestic violence, homes for street children, legal assistance for women and children, and strategies to deal with retrenched garment workers, among others; (C) Assistance given to women in slum areas who want to shift from being a garment worker to a safer and better job	Single Country	None
First Agreement on Trade Negotiations among Developing Member Countries of the Economic and Social Commission for Asia and the Pacific (Bangkok Agreement)	United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP)	6/17/1976	11/2/2005	First Agreement on Trade Negotiations among Developing Member Countries of the Economic and Social Commission for Asia and the Pacific (Bangkok Agreement) was entered into force on 17th June 1976 and amended on 2nd November 2005.	(A) Expansion of trade and economic cooperation by adopting mutually beneficial trade liberalization measure among the developing member countries of ESCAP to promote economic development; (B) Reduction of tariff and non-tariff duties; (C) Achievement an average non-MFN rate of 21.5 for garment and 4.25 for Fabrics	Multilateral Regional	Least Develop Countries

South Asia Development Facility of the International Financial Corporation (SEDF) Sector Strategy	International Finance Corporation	2003	2005	See Table 1 of the IFC Monitor Report.	(A) Aid given to 128 companies in the RMG sector in order to increase their participation in trade fairs and to improve their customer service; (B) Improvement of their productivity services by participating in job fairs and receiving advisory services from service providers supported by SEDF, including productivity improvement and restructuring; (C) Building the capacity of the two leading trade associations, BGMEA and BKMEA, to provide compliance-related services in order to improve the compliance of assisted companies with standards	Single Country	None
Direct Cash Incentives	Board of Investment, Bangladesh	7/1/2002	2005	The direct cash incentives for the use of local fabrics, knitted and woven alike, had been set at the beginning of the fiscal year of 2003, namely 1st July 2002, and was phased out in 2005 (Knappe 2002).	(A) Use of local fabrics for production of export entitles a cash subsidy amounting to 15% of the cost of the fabrics; (B) Before 2002 the cash incentive was 25%	Single Country	None
Agreement on Textile and Clothing (ATC)	World Trade Organization	1995	2005	ATC is not an extension of MFA but rather a ten-year transition between the former and the full integration of textiles and clothing into the multilateral trading system GATT.	(A) ATC is a transitory regime between the Multi Fibre Agreement (MFA), which came into force in 1974 and was renegotiated 4 times the last in 1994, and the full integration of textiles and clothing into GATT; (B) Minimum volume integrated in per cent of total volume of trade in textiles and apparel in 1990 was done in 4 steps over 10 years: 16% in 1995; 17% in 1998; 18% in 2002; and 49% in 2005 (see Table 5 of Nordås 2004 on page 13 for more details)	Multilateral (World)	US, EU, China, India, WTO members

Agreement on South Asian Association for Regional Cooperation (SAARC) Preferential Trading Agreement (SAPTA)	People's Republic of Bangladesh, Kingdom of Bhutan, Republic of India, Republic of Maldives, Kingdom of Nepal, Islamic Republic of Pakistan, Democratic Socialist Republic of Sri Lanka	4/11/1993	2005	The agreement was signed on 11th April 1993; it has been superseded by SAFTA on 1st January 2006.	(A) Arrangement of tariff, para-tariff, non-tariff, and direct trade measures following trade liberalization approaches and procedures such as product-by-product basis, across-the-board tariff reductions; sectoral basis; and direct trade measures (tariff preferences are initially done on a product-by-product basis); (B) Special consideration given to Least Developed Contracting States (LDCS), including Bangladesh, by means of technical assistance and cooperation arrangements (see Annex I of SAPTA); (C) Special treatment extended to LDCS wherever possible via duty-free access, removal of non-tariff barriers, removal of para-tariff barriers, negotiation of long-term contracts, safeguard measures	Multilateral (Regional)	India, Sri Lanka, Pakistan, Bhutan, Maldives, Nepal
Development Support Credit II	The World Bank, Government of People's Republic of Bangladesh, Ministry of Finance	7/27/2004	12/31/2004	Development Support Credit II runs from 27th July 2004 until 31st December 2004.	(A) Improvement of investment climate through maintaining macroeconomic stability, trade liberalization, and strengthening core governance function and performance of the banking industry also with the objective of increasing trade-GDP ratio and lower trade protection, as measured by nominal protection and Quantitative Restrictions; (B) Removes all quota restrictions and scaling down nominal and effective protections gradually; (C) Producing moderately satisfactory outcome with actual disbursed amount of SDR 136.8 M	Single Country	None

Appendix F

Cycles and Seasonality

F.1 Cycles and Seasonality

Case studies describe a characterization of the seasonal patterns of procurement and demand for ready made garment as follows.

The garment industry is characterized by short product life cycles, high differentiation and product variety, a volatile demand and long supply processes. Products can be divided roughly in three categories, according to their life cycle.

- Fashion products: 10 weeks product life, accounting for 35% of the market;
- Seasonal products: 20 weeks product life, accounting for 45% of the market;
- Basic products: sold throughout the year, accounting for 20% of the market.

Large specialised retailers (like J. C. Penney, H&M, GAP, etc.) tend to distinguish at least five seasons:

- Fall 1: Delivery to retailers in July/August;
- Fall 2: Delivery to retailers in September/October;
- Holiday: Delivery to retailers in October/Mid November;
- Spring: Delivery to retailers in Late January / March;
- Summer: Delivery to retailers in March / Mid April.

Retailers design process start around 40 weeks before the start of the season. High turnaround companies, such as H&M and Zara design just 17 weeks before the season. Production and transportation lead time adds up to an average of 3 months when sourcing is done in developing countries. Manufacturers usually label the products with the retailers' price tags, place the garments on hangers and bags if necessary and ship the product ready to be marketed.

F.2 Seasonality in our Dataset

The main products categories our empirical study looks at do not exhibit high seasonality, with volumes relatively constant over the year. There are only a few sub-categories that exhibit a distinguishable seasonal patterns, when looking at the large buyers purchases. The feature they all have in common is the material being wool, animal furs or synthetic analogs, which are typically winter-specific. These are detailed below. In the panel that we work with in chapter 2, these subcategories represent less than 0.002% of the traded volumes, so in most of the cases, no adjustments to our estimations are needed, besides standard seasonality controls.

Table F.1: Seasonal Products

Product Category	Quarters	First Season	Second Season
620311 Men's or Boys' Suits, of Wool or Fine Animal Hair	2	April-June	October-December
620323 Men's or Boys' Ensembles, of Synthetic Fibres	2	April-June	October-December
620329 Men's or Boys' Ensembles, of Other Textile Materials	2	January-March	April-June
620411 Women's or Girls' Suits, of Wool or Fine Animal Hair	3	January-March	April-June
620421 Women's or Girls' Ensembles, of Wool or Fine Animal Hair	3	January-March	April-June
620423 Women's or Girls' Ensembles, of Synthetic Fibres	3	January-March	October-December
620431 Women's or Girls' Jackets, of Wool or Fine Animal Hair	3	April-June	July-September
620441 Women's or Girls' Dresses, of Wool or Fine Animal Hair	1	April-June	-
620444 Women's or Girls' Dresses, of Artificial Fibres	1	April-June	-

TABLE F.2: Seasonality

	(1) ASDA	(2) CAND	(3) CARREFOUR	(4) GAP	(5) HANDM	(6) KMART	(7) LEVIS	(8) NEXT	(9) PRIMARK	(10) TESCO	(11) VANHEUSEN	(12) VF	(13) WALMART
season_2	0.171	0.177	0.917***	0.378*	-0.196	-0.159	0.046	0.078	-0.086	0.494***	-0.143	0.348*	-0.160
	(0.20)	(0.36)	(0.15)	(0.21)	(0.31)	(0.12)	(0.26)	(0.97)	(0.28)	(0.14)	(0.29)	(0.19)	(0.14)
season_3	0.254	0.313	0.264*	0.555	-0.111	0.105	0.302	0.327	0.452	0.381	0.416	0.179	0.141
	(0.33)	(0.38)	(0.14)	(0.34)	(0.42)	(0.28)	(0.29)	(0.92)	(0.33)	(0.25)	(0.29)	(0.26)	(0.14)
season_4	-0.051	0.171	0.962***	0.218	-0.317	-0.016	0.356	0.460	0.041	0.211	0.240	0.212	0.039
	(0.20)	(0.34)	(0.21)	(0.16)	(0.28)	(0.13)	(0.23)	(0.88)	(0.20)	(0.15)	(0.25)	(0.20)	(0.14)
Constant	16.325***	16.875***	15.682***	17.246***	18.206***	17.290***	16.620***	13.677***	16.254***	16.005***	17.008***	17.240***	17.539***
	(0.14)	(0.25)	(0.11)	(0.13)	(0.19)	(0.11)	(0.18)	(0.49)	(0.17)	(0.13)	(0.20)	(0.16)	(0.10)
Observations	31	31	31	31	31	31	31	26	31	31	31	31	31
R^2	0.057	0.027	0.634	0.140	0.026	0.056	0.090	0.012	0.126	0.221	0.160	0.091	0.163

TABLE F.3: Seasonality - With Trend

	(1) ASDA	(2) CAND	(3) CARREFOUR	(4) GAP	(5) HANDM	(6) KMART	(7) LEVIS	(8) NEXT	(9) PRIMARK	(10) TESCO	(11) VANHEUSEN	(12) VF	(13) WALMART
season_2	0.127	0.105	0.909***	0.334***	-0.264**	-0.177	0.001	-0.416	-0.138	0.483***	-0.193	0.310***	-0.151
	(0.16)	(0.10)	(0.15)	(0.11)	(0.12)	(0.13)	(0.18)	(0.54)	(0.13)	(0.13)	(0.12)	(0.10)	(0.14)
season_3	0.165	0.168	0.247	0.466**	-0.245	0.068	0.211	-0.050	0.347*	0.360	0.315**	0.104	0.160
	(0.21)	(0.13)	(0.15)	(0.21)	(0.24)	(0.25)	(0.19)	(0.39)	(0.19)	(0.22)	(0.14)	(0.15)	(0.14)
season_4	-0.096	0.098	0.954***	0.174	-0.384***	-0.034	0.311*	-0.363	-0.012	0.201	0.190	0.175	0.049
	(0.14)	(0.12)	(0.22)	(0.14)	(0.13)	(0.13)	(0.18)	(0.41)	(0.14)	(0.16)	(0.13)	(0.11)	(0.13)
quarter	0.044***	0.072***	0.008	0.045***	0.067***	0.019*	0.045***	0.165***	0.052***	0.011	0.050***	0.037***	-0.010
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	7.696***	2.865***	14.039***	8.570***	5.158**	13.686***	7.829***	-18.284***	6.092***	13.924***	7.271***	9.968***	19.386***
	(1.76)	(0.90)	(1.33)	(2.00)	(2.06)	(2.07)	(1.44)	(4.30)	(1.63)	(1.90)	(1.04)	(1.16)	(1.32)
Observations	31	31	31	31	31	31	31	26	31	31	31	31	31
R^2	0.644	0.900	0.655	0.660	0.750	0.224	0.710	0.789	0.746	0.278	0.839	0.729	0.260

Appendix G

Code

G.1 Matlab Code

What follows just includes the source file for the Monte Carlo exercise presented in Chapter 4. This file, itself calls about 25 *child* functions nested in one another and these are not included here in the interest of space. All the code and supporting files are available upon request. Consider that the actual Monte Carlo (Chapter 4) was ran accessing a cluster with 1800 Westmere cores (150 nodes) with 24GB of RAM, plus 11 nodes with 48 cores and 512 GB of RAM. For this reason, the code below was fragmented to use 100 cores simultaneously and it is included here for illustrative purposes only. Running this on a single computer as it is written here is virtually impossible.

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% MPE Computation and Monte Carlo Exercise of Network Formation Game with
% Endogenous Bargaining.
%
%                                                    by Julia Cajal Grossi
%
% (Please do not circulate)
% (Last Updated: July 2014)
% (See draft paper)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% ======================================================================= %
%                          INDEX OF THIS FILE
%
% I) FORMAT OF THE DATA
% II) PRESENTATION OF THE MONTE CARLO EXERCISES
% III) CONSTANTS AND SEEDS
% IV) COMPUTING AN MPE OF THE GAME
% V) SIMULATION OF DATA COMING FROM THAT MPE
% VI) CALLING ESTIMATION PROCEDURES
%   VI-A) CCPs
```

```
%    - Frequency with random assignments for unobserved;
%    - Kernel (discrete / continuous);
%    - Frequency with unconditional CPs imputed to unobserved;
%    - Frequency with same probability imputed to unobserved;
%   VI-B) FORWARDS SIMULATION
%   VI-C) PARAMETERS (STRUCTURAL ESTIMATION L&F)
% VII) MONTE CARLO
% VIII) SAVING RESULTS AND STATISTICS
%
% ====================================================================== %

% ====================================================================== %
% I. FORMAT OF THE DATA:
% ====================================================================== %

% Matrix of size T x (1+(2xB)) where:
% T: to the total number of realisations of the network;
% (:,1): first column has the time indices;
% (:,2:B+1): following B columns, one for each buyer, with the index of
% the seller, j, buyer i is linked to;
% (:, B+2:2B+2): prices paid by each buyer, to its partner;

% Matrix of size 3 x B where:
% (1,:): Q(i), quantities for each buyer;
% (2,:): R(i), revenues (price in local market) for each buyer;
% (3,:): M(i), cost of material inputs for buyer;

% Matrix of size T x (B+S) where:
% each entry ==1 if the player is active (trading) in that period, zero
% otherwise.

% ====================================================================== %
% II. PRESENTATION OF THE MONTE CARLO:
% ====================================================================== %

% Constants remain as above. The implementation is for one market only.

% Specifics of the equilibrium in next section.

% Number of Monte Carlo simulations for every experiment:
MCS = 1000;

% Time periods (T):
% T = 50; % size(Data,1);

% Parameter vector: (for 2 buyers, 2 sellers)

% --> (:,1): Cost of linking with old seller;
% --> (:,2): Cost of linking with new seller;
% --> (:,3): Bargaining parameter for buyer 1;
% --> (:,4): Bargaining parameter for buyer 2;
% --> (:,5): Heterogeneity of seller 1;
% --> (:,6): Heterogeneity of seller 2;

% Setting 2: Costs of linking; no heterogeneity; symmetric.
```

```
theta_2 = [1 12 0.5 0.5 2 0.2 0.2 1];  %% OK


% ====================================================================== %
% III. CONSTANTS AND SEEDS:
% ====================================================================== %

% 0) Choice of experiment:
theta = theta_2;
    % Rename parameters:
    B_ij = zeros(1,2); % --> Two buyers
        B_ij(:,1)= theta(:,3);
        B_ij(:,2)= theta(:,4);
    c_low = theta(:,1);
    c_high = theta(:,2);
    Rho_j = zeros(2,3); % --> Two sellers
        Rho_j(1,1)=theta(:,5);
        Rho_j(1,2)=theta(:,6);
        Rho_j(2,1)=theta(:,7);
        Rho_j(2,2)=theta(:,8);
        %Rho_j(1,3)=theta(:,9);
        %Rho_j(2,3)=theta(:,10);

% 1) PLAYERS:
B = 2; % Total Number of Buyers --> Load from data
S = 2; % Total Number of Sellers --> Load from data --> back to 3

% 2) STATES AND ACTIONS:
% Given the Players in the game, generate the states of the world and
% relevant matrices:
[Proposals, B_Actions, A_b, states, Move, G, Cou
nterfactuals, Gamma] = states_generator(B, S);
        % --> This functions calls procedu
        % re npermutek.m, which is NOT written by me.
        % Available in Mathworks.
% If you cannot call npermutek, generate states as follows:
% Proposals=zeros(states,B);
% for i=1:B
% Proposals(:,i)=kron(kron(ones((B_Actions^(i-1)),1),
% cumsum(ones(1,B_Actions))'), ones(B_Actions^(B-i),1));
% end

% 3) PARAMETERS IN THE PROFIT FUNCTIONS AND BARGAINING GAME

    beta=0.9; % Discount factor

    % Quantities and Inputs --> Load from data
    Q = [2 2]; % load(); % 2*(B,1); % Quatinties for each buyer.
    M = 2*ones(B,1); % load(); % 2*ones(B,1); % Cost of material inputs per unit.
    R = 100*ones(B,1); % load(); % 100*ones(B,1); % Per-unit revenue for the
    buyer.
    mkt_price = 90; % Per unit price of the garment as outside option for the
    buyer.

    % Costs of Linking
```

```
    Costs_of_linking = c_high*ones(B_Actions,B_Actions); % --> rows are actions.
    Costs_of_linking = Costs_of_linking + (-c_high+c_low)*eye(B_Actions,B_Actions
    );
    Costs_of_linking(B_Actions,:)= zeros(1,B_Actions);
    % If the buyers chooses not to link, no cost; If he chooses to link with an
    % existing supplier, c_low; if he chooses to link with a new supplier,
    % c_high. Same for all buyers.

% 4) MPE ITERATION CONTROLS
rho_cutoff=0.000625; % convergence cutoff criterion in
%the iteration over probabilities in MPE computation;
max_iter = 1000; % maximum number of iterations that
%will be allowed in the MPE "Outer" Loop

% 5) UNOBSERVABLES AND SHOCKS
sigmaeps=1;

% 6) VARIOUS SEEDS AND INITIALISATIONS
V_i=zeros(states,B); % Value function for the buyers
Vs_i=zeros(states,S); % Value function for the sellers
T_nash=(5*ones(B,S,states)).*G(:,1:S,:); % Prices for all players
P_i_a_g=1/B_Actions*ones(B,B_Actions,states); % Initialising CCPs
% stable_links=G; % Stability initial condition (all links are stable)
%seed=rng; %
%rng=seed;

% 7) FORWARD SIMULATION ITERATION CONTROLS
MAXITER = 500; % Maximum number of iteration in the fixed point problem (prices
    to values)
paths = 500; % Paths is the number of different paths,
% starting from a network, that the forward simulation
% will follow to average over and get the value functions.
T = 80; % the length of each path;
rho_cutoff_fs = 0.009; % cutoff for the fixed point problem (prices to value
    functions).

% 8) SECOND STAGE CONTROLS
prob_diff_cutoff = 0.0001; % cutoff for the policy iteration in the second stage.
%Careful: Increasing this slows down the second stage consideraby.

% ======================================================================= %
% IV. COMPUTING AN MPE OF THIS GAME:
% ======================================================================= %

% Idenitfy the Setting to work with
name = num2str(theta);
char('Computation of MPE - Experiment Setting: ',
'Costs of Linking, Bargaining Parameters, Match quality', name)
% Given constants and parameters above, compute an MPE of the game:
[Converge, Convergence_Path, Lim_Cycle_period, iter_MPE, Psteady_MPE,
Prices_MPE, CCPs_MPE, Gamma_MPE, Trans_MPE, V_i_MPE, Vs_i_MPE] = Generate_MPE(
    rho_cutoff,
max_iter, B, S, B_Actions, states, Proposals, G, Counterfactuals, Move, P_i_a_g,
sigmaeps, V_i, Vs_i, T_nash, M, Q, R, beta, mkt_price, Costs_of_linking, B_ij,
    Rho_j, Gamma);
```

```

% ----------------------------   Outputs: ------------------------------- %
% --> Converge: Scalar = 0 if cnvergence not achieved.
%                      = 1 if convergence achieved.
% --> iter_MPE: Number of iterations until convergence.
%               (max_iter if Convergence=0)
% --> Convergence_Path: max_iter x 1 vector storing
%                the deviation in each loop until hitting the cutoff for convergence.
%               (zeros for the iterations never visited)
% --> Lim_Cycle_Period: scalar; contains the number of points
%                the loop visits if it has not cobverged to a solution but to a cycle.
%               (if convergence, this is zero)
% --> Psteady_MPE: states x 1; contains the ergodic distribution of states.
%               (if no convergence, zeros everywhere)
% --> Prices_MPE: matrix of size states x B containing the
%                price paid by buyer (column) for the garment under each state (row).
%               (if no convergence, just shows last iteration)
% --> CCPs_MPE: matrix of size states x (B*B_Actions) containing the CCPs
%                for each player and action (columns) under each state (rows).
%               (if no convergence, just shows last iteration)
% --> Gamma_MPE: vector of size states x 1 containing the stable
%                network in the Gamma stability mapping.
%                (if no convergence, just shows last iteration)
% --> Trans_MPE: matrix of size states x states with the equilibrium
%                transitions over states.
%               (if no convergence, just shows last iteration)
% --> V_i_MPE: matrix of size states x B with the value functions for
%                each buyer under each state.
%               (if no convergence, just shows last iteration)
% --> Vs_i_MPE: matrix of size states x S with the value functions
%                for each seller under each state.
%               (if no convergence, just shows last iteration)

% --------------------   Embedded Procedures: --------------------------- %
% The Generate_MPE function calls the following procedures:
% --> probability_objects: Given CCPs generates transitions
%       over states and choice-conditional transitions;
% --> sellers_choice: Selects the link of max profit
%    when seller is linked to more than one buyer and gives the
%      stability rules;
% --> stage_profits_buyer: Computes stage profits of the buyers
%       given the stability rules;
% --> value_function_updating: Generates value functions for all
%      players via value function iteration;
% --> pricing_problem: Solves the Nash Bargaining problem for
%      all linked pairs, in turn calling:
%          --> outside_options: Computes outside options for all
%             players given the negotiation network.

% ====================================================================== %
% V. SIMULATING DATA FROM THAT MPE:
% ====================================================================== %
```

```
% ARGUMENTS FOR THE SIMULATION FUNCTION:
nobs = 2000; % Number of "observations"
psteady = Psteady_MPE; % vector states x
% 1 with the steady state probabilities
CCPs_MPE; % array of size B x Actions x
% states with the equilibrium conditional choice probabilities
B; % As described above
states; % As decribed above
B_Actions; % As described above
seed; % Generated above

[~, Net_Choices_sim] = simulation_MPE(nobs, CCPs_MPE ,
psteady, B, B_Actions,states, seed, G);

Net_Stream_sim=zeros(nobs,1);
for n=1:nobs,
    for s=1:states,
        if Proposals(s,:)==Net_Choices_sim(n,:),
            Net_Stream_sim(n,1)=s;
        end
    end
end

% ======================================================================== %
% VI. ESTIMATION PROCEDURES:
% ======================================================================== %

% ===========================   VI-A) CCPs   =========================== %

[P_i_a_g_A, P_i_a_g_B, P_i_a_g_C, P_i_a_g_D, P_i_a_g_E,
 P_i_a_g_F] = CCPs(B, B_Actions, S, states, Net_Choices_sim, R, Net_Stream_sim);

%   - Frequency with random assignments for unobserved (with and without cutoff);
%   - Kernel (discrete / continuous);
            % Kernel estimator for continuous state variable;
            % Kernel estimator for discrete state variable;
%   - Frequency with unconditional CPs imputed to unobserved;
%   - Frequency with same probability imputed to unobserved;

% =====================  VI-B) FORWARDS SIMULATION ==================== %

P_i_a_g = zeros(B, B_Actions, states);
for n=1:states,
    for i=1:B,
        for a=1:B_Actions,
        P_i_a_g(i,a,n) = CCPs_MPE(n,(a+(B_Actions*abs(B-i-1))));
        end
    end
end

% Initial arbitrary stability rule
Gamma_tau = Gamma_MPE;

stable_links = G;
```

```
for n=1:states,
    stable_links(:,:,n) = G(:,:,Gamma(n));
end

T_tau=(5*ones(B,S,states)).*G(:,1:S,:);
 for n=1:states,
     for i=1:B,
         for j=1:S,
            T_tau(i,j,n)=Prices_MPE(n,i)*stable_links(i,j,n);
         end
     end
 end

V_i=V_i_MPE;
Vs_i=Vs_i_MPE;

[conv_vec_fs, Vs_i_star, V_i_star, T_nash_star, Gamma_star] = ForwardsSimulation(
    V_i,
Vs_i, Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, paths, T, B, S, B_Actions, states
    ,
Proposals, G, R, Rho_j, M, Q, mkt_price, Costs_of_linking, beta,
Counterfactuals, B_ij, Move, P_i_a_g);

% Alternative 1: Solve for prices computing an MPE of the game and do not
% update prices in the forwards simulation (so no convergence), just the
% simulation.

% Alternative 2: leave the fixed point in prices and run the full
% convergence exercise.


% =========================  VI-C) PARAMETERS ========================= %

P_i_a_g = P_i_a_g_E; % Or choose alternative

% TRUE PARAMETER VECTOR: [1 12 0.6 0.5 2 0.2 0.2 1]

% ALTERNATIVE 1: SCAN A GRID

CANDIDATES_VEC;

% ALTERNATIVE 2: MINIMIZATION:

[LF_estimates,fval,flag]=fminsearch(@(theta)  minimize(theta, P_i_a_g,
prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau, rho_cutoff_fs, MAXITER,
B, S, B_Actions, states, paths, T, Proposals, G, R, M, Q,
mkt_price, beta, Counterfactuals, Move), [0.2 15 0.5 0.6 0 0.2 0.2 0]);

% ====================================================================== %
% VII. MONTE CARLO:
% ====================================================================== %

% Runs with variations in first and second stage:

        % Frist stage:
```

```
            % A) P_i_a_g_A: simple frequency estimator (1 to 4)
            % B) P_i_a_g_D: frequency estimator with kernel (5 to 8)
            % C) P_i_a_g_E: frequencies with unconditional assumption (9 to
            % 12)
            % D) P_i_a_g_F: frequencies with all actions same proba (13 to
            % 16)
            % E) P_i_a_g_G: True probabilities (16 to 20)

        % Second stage:
            % A) Use all states and treat prices as unknown
            % B) Use all states and exploit observed prices
            % C) Use observed states and treat prices as unknown
            % D) Use observed states and exploit observed prices

nexper = 5*4; % 20 EXPERIMENTS
RESULTS_MATRIX = zeros(100,8,nexper);

% Grid of candidate parameters to scan:
CANDIDATES_VEC;
for repli=1:1000 % 1000 runs for each estimator

%%%%%%%%%%%%%%%%%%%%%%%%%%% GENERATE SAMPLE %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

nobs = 2000; % Number of "observations"
psteady = Psteady_MPE; % vector states x 1 with
% the steady state probabilities
CCPs_MPE; % array of size B x Actions x states with
% the equilibrium conditional choice probabilities
B; % As described above
states; % As decribed above
B_Actions; % As described above
%seed; % Generated above

[~, Net_Choices_sim] = simulation_MPE(nobs, CCPs_MPE
, psteady, B, B_Actions,states, G);
% Note that in actual data I don't observe the
%action, but I infer it from the evolution of states

Net_Stream_sim=zeros(nobs,1);
for n=1:nobs,
    for s=1:states,
        if Proposals(s,:)==Net_Choices_sim(n,:),
            Net_Stream_sim(n,1)=s;
        end
    end
end

Observed_states=zeros(states,1);
for s=1:states
    for n=1:nobs
        if Net_Stream_sim(n,1)==s
       Observed_states(s,1) = Observed_states(s,1)+1;
        end
    end
end
```

```
Observed_states(:,1) = (Observed_states(:,1)>0);
Prices_MPE;

%%%%%%%%%%%%%%%%%%%%% RUN ALTERNATIVE FIRST STAGES %%%%%%%%%%%%%%%%%%%%%%%%

[P_i_a_g_A, ~, ~, P_i_a_g_D, P_i_a_g_E, P_i_a_g_F] = CCPs(B,
B_Actions, S, states, Net_Choices_sim, R, Net_Stream_sim);

P_i_a_g_G = zeros(B, B_Actions, states);
for n=1:states,
    for i=1:B,
        for a=1:B_Actions,
        P_i_a_g_G(i,a,n) = CCPs_MPE(n,(a+(B_Actions*abs(B-i-1))));
        end
    end
end


%%%%%%%%%%%%%%%%%%%% RUN ALTERNATIVE SECOND STAGES %%%%%%%%%%%%%%%%%%%%%%%%

for exper = 1:nexper
%
%          if exper<=4
%              base = 1;
%              P_i_a_g = P_i_a_g_A;
%                      % A) P_i_a_g_A: simple frequency estimator
%
%                  if exper == base % A) Use all states and treat prices as
    unknown
%                  [MinObjFun, Beta] = Structural_Estimation_LF(CANDIDATES_VEC,
%                 P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau,
%                 rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths, T,
%                 Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals, Move);
%                  RESULTS_MATRIX(repli,:,exper)= Beta;
%                  end
%
%                  if exper == base+1 % B) Use all states and exploit observed
    prices
%                  [MinObjFun, Beta] = Structural_Estimation_LF_obs(
    Observed_states,
%                 Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i,
%                 Vs_i, Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
%                 states, paths, T, Proposals, G, R, M, Q, mkt_price, beta,
%                 Counterfactuals, Move);
%                  RESULTS_MATRIX(repli,:,exper)= Beta;
%                  end
%
%                  if exper == base+2 % C) Use observed states and treat prices as
     unknown
%                  [MinObjFun, Beta] = Structural_Estimation_LF_res(
    Observed_states,
%                     CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i,
    Gamma_tau, T_tau,
```

```
%                     rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths, T, Proposals,
%                     G, R, M, Q, mkt_price, beta, Counterfactuals, Move);
%                  RESULTS_MATRIX(repli,:,exper)= Beta;
%                  end
%
% %                  if exper == base+3  % D) Use observed states and exploit observed prices
% %                  [MinObjFun, Beta] = Structural_Estimation_LF_obs_res(Observed_states,
% %                     Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau,
% %                     T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths, T,
% %                     Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals, Move);
% %                  RESULTS_MATRIX(repli,:,exper)= Beta;
% %                  end
%
%          end

        if exper>4 && exper<=8
            base = 5;
            P_i_a_g = P_i_a_g_D;
                  % B) P_i_a_g_D: frequency estimator with kernel

                    if exper == base % A) Use all states and treat prices as unknown
                    [MinObjFun, Beta] = Structural_Estimation_LF(CANDIDATES_VEC,
                     P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau,
                     rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                     T, Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals, Move);
                    RESULTS_MATRIX(repli,:,exper)= Beta;
                    end

                    if exper == base+1 % B) Use all states and exploit observed prices
                    [MinObjFun, Beta] = Structural_Estimation_LF_obs(Observed_states,
                     Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i,
                      Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
                      states, paths, T, Proposals, G, R, M, Q, mkt_price, beta,
                      Counterfactuals, Move);
                    RESULTS_MATRIX(repli,:,exper)= Beta;
                    end

                    if exper == base+2 % C) Use observed states and treat prices as unknown
                    [MinObjFun, Beta] = Structural_Estimation_LF_res(Observed_states,
                    CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau,
                     T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                      T, Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals,
                       Move);
                    RESULTS_MATRIX(repli,:,exper)= Beta;
                    end
```

```
%                 if exper == base+3  % D) Use observed states and exploit
    observed prices
%                 [MinObjFun, Beta] = Structural_Estimation_LF_obs_res(
    Observed_states,
%                Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i
    ,
%                Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
%                states, paths, T, Proposals, G, R, M, Q, mkt_price,
%                beta, Counterfactuals, Move);
%                 RESULTS_MATRIX(repli,:,exper)= Beta;
%                 end

        end

        if exper>8 && exper<=12
            base = 9;
            P_i_a_g = P_i_a_g_E;
                    % C) P_i_a_g_E: frequencies with unconditional assumption

                if exper == base % A) Use all states and treat prices as unknown
                [MinObjFun, Beta] = Structural_Estimation_LF(CANDIDATES_VEC,
                 P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau,
                  rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                   T, Proposals, G, R, M, Q, mkt_price, beta,
                    Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+1 % B) Use all states and exploit observed
    prices
                [MinObjFun, Beta] = Structural_Estimation_LF_obs(Observed_states,
                 Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff,
                  V_i, Vs_i, Gamma_tau, T_tau, rho_cutoff_fs, MAXITER,
                   B, S, B_Actions, states, paths, T, Proposals, G,
                    R, M, Q, mkt_price, beta, Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+2 % C) Use observed states and treat prices as
    unknown
                [MinObjFun, Beta] = Structural_Estimation_LF_res(Observed_states,
                CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau,
                T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                 T, Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals, Move
    );
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

%                 if exper == base+3  % D) Use observed states and exploit
    observed prices
%                 [MinObjFun, Beta] = Structural_Estimation_LF_obs_res(
    Observed_states,
%                Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i
    ,
```

```
%                 Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states
,
%                  paths, T, Proposals, G, R, M, Q, mkt_price, beta,
    Counterfactuals, Move);
%                   RESULTS_MATRIX(repli,:,exper)= Beta;
%                   end

        end

        if exper>12 && exper<=16
            base = 13;
            P_i_a_g = P_i_a_g_F;
                     % D) P_i_a_g_F: frequencies with all actions same proba

                if exper == base % A) Use all states and treat prices as unknown
                [MinObjFun, Beta] = Structural_Estimation_LF(CANDIDATES_VEC,
                 P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau,
                 rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                  T, Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals,
    Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+1 % B) Use all states and exploit observed
    prices
                [MinObjFun, Beta] = Structural_Estimation_LF_obs(Observed_states,
                Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i,
                 Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
                 states, paths, T, Proposals, G, R, M, Q, mkt_price, beta,
                 Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+2 % C) Use observed states and treat prices as
    unknown
                [MinObjFun, Beta] = Structural_Estimation_LF_res(Observed_states,
                CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau,
                T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                 T, Proposals, G, R, M, Q, mkt_price, beta, Counterfactuals, Move
    );
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

%                   if exper == base+3  % D) Use observed states and exploit
    observed prices
%                   [MinObjFun, Beta] = Structural_Estimation_LF_obs_res(
    Observed_states,
%                  Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i
,
%                   Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
    states,
%                   paths, T, Proposals, G, R, M, Q, mkt_price, beta,
    Counterfactuals, Move);
%                   RESULTS_MATRIX(repli,:,exper)= Beta;
%                   end
```

```

        end

        if exper>16 && exper<=20
            base = 17;
            P_i_a_g = P_i_a_g_G;
                       % E) P_i_a_g_G: True probabilities

                if exper == base % A) Use all states and treat prices as unknown
                [MinObjFun, Beta] = Structural_Estimation_LF(CANDIDATES_VEC,
                 P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau, T_tau,
                 rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                  T, Proposals, G, R, M, Q, mkt_price, beta,
                   Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+1 % B) Use all states and exploit observed prices
                [MinObjFun, Beta] = Structural_Estimation_LF_obs(Observed_states,
                 Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i,
                  Gamma_tau, T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions,
                  states, paths, T, Proposals, G, R, M, Q, mkt_price, beta,
                  Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

                if exper == base+2 % C) Use observed states and treat prices as unknown
                [MinObjFun, Beta] = Structural_Estimation_LF_res(Observed_states,
                 CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff, V_i, Vs_i, Gamma_tau,
                  T_tau, rho_cutoff_fs, MAXITER, B, S, B_Actions, states, paths,
                   T, Proposals, G, R, M, Q, mkt_price, beta,
                   Counterfactuals, Move);
                RESULTS_MATRIX(repli,:,exper)= Beta;
                end

%                 if exper == base+3  % D) Use observed states and exploit observed prices
%                 [MinObjFun, Beta] = Structural_Estimation_LF_obs_res(Observed_states,
%                    Prices_MPE, CANDIDATES_VEC, P_i_a_g, prob_diff_cutoff,
%                    V_i, Vs_i, Gamma_tau, T_tau, rho_cutoff_fs, MAXITER,
%                    B, S, B_Actions, states, paths, T, Proposals, G, R,
%                     M, Q, mkt_price, beta, Counterfactuals, Move);
%                 RESULTS_MATRIX(repli,:,exper)= Beta;
%                 end

        end


end

end
```

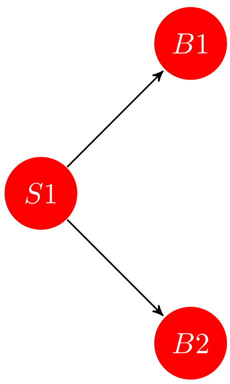
Appendix H

An Example Illustrating Endogenous Outside Options

H.1 Varying Marginal Costs

This section offers a very simple exposition of a small static 2×1 game, with a fixed network under different specifications of the outside options [1].

Consider a setting with 2 buyers, b_1 and b_2, with a value for the good equal to R, a unit demand and an outside option of value zero. Assume there is a unique seller, s, who can supply one unit of the good with an overall production cost of c_1 and two units with the cost c_2, where $c_1 < c_2$. For simplicity, fix all bargaining parameters to be equal to 0.5 so surplus is distributed equally across bargaining parties. Consider an exogenously determined negotiation network, g that looks as follows:



[1] This section, as well as important modifications in the specification of the general bargaining model presented in this paper, were motivated by very fruitful discussions with Ariel Rubinstein, whose comments are gratefully acknowledged. All mistakes are mine.

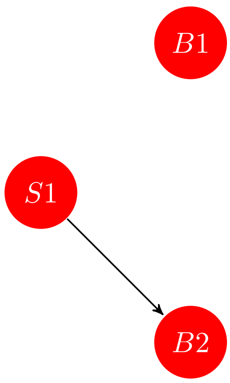
Focus on the bargaining outcome for the pair $b_1 - s$. The surplus for b_1 in this relation is given by $R - t_{b_1 s}$. The surplus for the seller in this setting is $(t_{b_1 s} + t_{b_2 s} - c_2) - (t_{\hat{b_2 s}} - c_1)$, where $t_{\hat{b_2 s}}$ is the counterfactual price s would obtain from b_2 if b_1 and s were not trading. Different specifications on $t_{\hat{b_2 s}}$ are possible.

H.1.1 The no-renegotiation assumption

One possible specification assumes no renegotiations are possible after disagreement takes place, so $t_{\hat{b_2 s}} = t_{b_2 s}$ and the counterfactual price with b_2 in the bargaining problem between b_1 and s is equivalent to the equilibrium price with b_2 under agreement. Under the parametrisation above, $t^*_{b_1 s} = \frac{R+c_2-c_1}{2}$. Note that in this case, the price agreed on with b_2 plays no role in the determination of $t_{b_1 s}$.

H.1.2 Allowing for a network effect

Alternatively, it could be the case that if the link $b_1 - s$ was to break, the price s would obtain from b_2 would be different from $t_{b_2 s}$, as the network on which b_2 and s would be barging would be:



In this context, $t_{b_2 s} = \frac{R+c_1}{2}$. If this is taken into account as the counterfactual scenario for the seller in the negotiation with b_1 when the links with both buyers are active, then $t^{*'}_{b_1 s} = \frac{1}{2}(R + \frac{2c_2-c_1}{3})$.

It can be seen that whenever $c_2 > 2c_1$, $t^*_{b_1 s} > t^{*'}_{b_1 s}$. Under this specification, with constant marginal costs (so $c_2 = 2c_1$), both specifications for the outside option of the seller would render the same result. Departures from that case then, would have an implication on the equilibrium prices and gains from trade.

H.2 Capacity Constraints

Now, assume that the seller can only produce one unit a cost c. A network with two edges like the one above cannot arise and the bargaining process ends breaking one or other link. Now, the surplus from the relationship $b_1 - s$ for the buyer is given again by $R - t_{b_1 s}$. The surplus for the seller is now $(t_{b_1 s} - c) - (max\{\hat{t_{b_2 s}} - c; 0\})$, where $\hat{t_{b_2 s}}$ is the counterfactual price s would obtain from b_2 if b_1 and s were to break their link. Note that if $\hat{t_{b_2 s}} - c < 0$, $t^*_{b_1 s} = \frac{R-c}{2}$. Whenever that inequality condition is reverted, it can be easily seen that $t^*_{b_1 s} = R$ and the seller extracts all the surplus of the relationship.

However, if, as before, $\hat{t_{b_2 s}}$ was to be specified in the counterfactual network arising from deleting the link with b_1 and bargaining only with b_2, then $\hat{t_{b_2 s}} = \frac{R+c}{2}$ and $t^{*'}_{b_1 s} = \frac{3R+c}{4}$. It can be easily seen that whenever $c > R$, trade between b_1 and s will not occur. But whenever $c < R$, the equilibrium price will be strictly smaller than R, so s will not be able to capture the whole of the gains from trade.

Generalising this result to a case in which the seller is linked to B buyers, $t^*_{bs} = \frac{2^B R+c}{2^B}$, which approaches $t^*_{bs} = R$ as B grows large. Extensions allowing for heterogeneity in players' outside options, reservations and costs are straightforward.

Appendix I

Measuring Unobserved Heterogeneity: Data Restrictions and Estimation

I.1 Input Costs

The first restriction we face when using fixed effects to recover the *types* of the manufacturers is the lack of information on labour inputs. We know from our visits to Bangladesh that for the set of products we are considering, the technology is fairly similar across firms. We have no information, however, on whether there are differences across firms on the quality or skills of their workers or the wages they offer. Below I present a very crude approximation to the share of labour in the cost of production of garments.

Table I.1: Share of (line) labour costs in costs of garment - Lower bound approximation

	Mins Per Kilo	Cost of Labour	Cost of Fabric	Share of Labour
Product	Median	USD	USD	%
Jacket	60.78	0.27	11.04	2.40
Shirt	19.34	0.09	7.50	1.14
Trouser	30.36	0.14	9.80	1.36

Minutes per kilo: Median of minutes (SMVs) in the production line by product taken over all the orders that 20+ firms received over a year; both estimated and actual times were used. Cost of Labour estimated using a monthly wage of USD61. Cost of Fabric: Estimated using a fabric-to-output weight ratio of 1 and prices of fabric for the 25th percentile of prices in Bangladesh Local.

The table above shows that the share of labours cost in the line over material + labour costs is between 1 and 2.4%. Although this is very limited exercise (in various ways, for example, it includes only minutes in the line and excludes the times of managers, etc.)

and needs to read with utmost caution, it offers a rough idea on orders of magnitude of fabric and labour.

Consistent with the picture we present here, in 2006 an ILO/UNDP project (BGD/85/153) estimated the overall average minutes-person required for the production of a piece of garment (including all the labour in basic worker equivalence) to be 25 in Bangladesh (for comparison, 19.7 in Hong Kong, 20 in Korea). If in a kilo of garment there were 6 items (which would be, for example, the case for very light shirts), the resulting estimation of labour requirement would be more than twice the minutes I have estimated in the table above and still the overall cost of labour would have a share over the cost of material inputs + labour below 7% [1].

A more systematic study was carried out by Kee (2006), who using a World Bank survey on 1,000+ firms estimated productivity in the sector finding coefficients of 0.01 for capital, 0.23 for labour and 0.76 for material inputs.

Turning to material inputs, the nature of our data is such that we only observe imported fabric, but not the fabric that is domestically procured. The selection of products we are working with eases off the challenges that this might impose, as we know there is nearly no local production of woven fabrics for the categories we consider. However, we have no information on whether third parties import fabric and re-sell domestically.

Out of the 7,800 manufacturers operating before 2012 in the whole of the panel (all products), about 2,900 import fabric at some point in the panel. There manufacturers cover 91% of all the export transactions in garment and 94% of the value of all exports. Moreover, more than 902% of the export transactions of the woven garment manufacturers in this subgroup are matched with at least one import transaction.

The weight of the exported garment consists mainly of the fabric needed to produce them, so the theoretical input-to-output ratio of weights is around one. Out of the 2,700, the median seller has a ratio of 0.5. However, if we restrict the sample to those producers that are more specialized in woven (i.e. that at least half of the value of their exports corresponds to woven products – a total of almost 1,400 sellers) that median is above 0.8 (and 1% is 0.61) [2]. These specialized sellers cover more than 75% of the

[1] The wages used in the ILO study correspond to 0.22 dollars per hour in Bangladesh, compared to 0.55 in China, 0.51 in India. Also, the wage of a chief quality controller (top of the scale) is 3.2 times the wage of an unskilled worker.

[2] The exact input-to-output weight ratio can be a characteristic of the exported product. For example, coats and jackets with zips, buttons, etc. have added weight in the final product that does not come from fabric. Controlling for the exported product should, among other things, take care of the "average" technical relation between the fabric weights and the output weight. Having controlled for that, low ratios can also represent firms that have a higher proportion of domestically sourced inputs. Verhoogen and Kugler (2009) show that a) prices of inputs are a good proxi for the quality of the inputs (i.e. do not reflect differences in transportation costs) and b) that plants purchasing high quality imported inputs also purchase high quality domestic inputs. They observe a high and robust correlation between the

exports of woven products.

To assess whether there is a domestic re-sell market of imported fabric, I considered all the imports of fabric (of any kind) coming into Bangladesh (without restrictions on the importing firm. The table below shows three facts: (i) of all the imports of fabric in Bangladesh, 96% are done by exporters (not only RMG, but firms that export in any category); (ii) 95% of all the imported fabrics is imported directly by RMG manufacturers; (iii) from the remaining imports of fabrics, only 1.8% corresponds to firms that could potentially supply fabric locally for RMG manufacturers [3].

TABLE I.2: Importers of Relevant Inputs

	Fabric
Percentages over all Exports	
Imported by Non-Exporters	0.038
Imported by Exporters	0.962
Percentages over all exports imported by Exporters	
Woven Garments	0.817
Knitted Garments	0.133
Textile Articles (linen, blankets, etc.)	0.018
Cotton, yarn and woven fabrics*	0.012
Minerals and oils	0.003
Special fabrics*	0.003
Textiles for Industrial Use	0.003
Knitted Fabrics*	0.002
Yarns and man-made fibres*	0.000

I.2 Estimation

Consider that prices can be decomposed as in the equation above and that we now change the notation slightly so matrix X collects the time and product fixed effects, we drop the k subindex and stack observations over time and i:

$$\tilde{y} = \tilde{X}\beta + \tilde{D}\theta + \tilde{F}\psi + \tilde{\epsilon} \tag{I.1}$$

where D is $N{*}{\times}N$ and is the design matrix for sellers effects, F is $N{*}{\times}J$ and collects the buyer effects and X contains M columns, one for each regressor. With T_i observations per individual (assuming away the different k's for ease of notation), $N{*} = \sum_i T_i$. The statistical error is assumed to have a zero mean, a finite variance and to be orthogonal to all other effects in the model. Dummy variables are included for all the buyers and the seller effect are swept out via within transformation, so $\tilde{D}$ becomes the null matrix.

prices of domestic inputs and imported inputs. Therefore, using the price of the imported input and controlling for the input-to-output ratio seems to be sufficient for accounting for unit input costs.

[3]Categorisation of importers in sub-sector is done using the main product exported by the firm.

The notation above corresponds to one-to-one matching, because it gets cumbersome to represent the matrices otherwise. But Abowd and Stinson (2003) present a complete exposition that allows for many-to-many matching during the same period and with a third level in the panel section (the product).

$$y = F\psi + X\beta + \epsilon \tag{I.2}$$

It is shown in Abowd et al. (2002) that this is algebraically equivalent to introducing dummy variables for both sets of players. Estimation of the full model by fixed effects methods requires a special algorithm to deal with the high dimensionality of the problem. So the matrix system will be solved by re-arranging the rows and columns in the matrices to have the players ordered according to their "component" of the network. So groups are defined to contain the maximally connected subgraphs of the graph and the groups block-diagonalise the matrix (with $X'X, X'F, F'X, F'F$) and with each group, all but one fixed effect can be estimated. Then, the sellers that don't change firms have zeros in their entries of the F matrix, so the computation will use the information on all the players for $X'X$ and only on those groups that have "movers" for the rest of it.

For concreteness, the estimation starts by performing the within transformation over i, and then the system to be solved is:

$$\begin{bmatrix} X'X & X'F \\ F'X & F'F \end{bmatrix} \begin{bmatrix} \beta \\ \psi \end{bmatrix} = \begin{bmatrix} X'y \\ F'y \end{bmatrix} \tag{I.3}$$

which is:

$$\left[\begin{bmatrix} X'X & 0 \\ 0 & 0 \end{bmatrix} + \sum_{i \in Movers} \begin{bmatrix} 0 & X'F \\ F'X & F'F \end{bmatrix} \right] \begin{bmatrix} \beta \\ \psi \end{bmatrix} = \begin{bmatrix} X'y \\ 0 \end{bmatrix} + \sum_{i \in Movers} \begin{bmatrix} 0 \\ F'y \end{bmatrix} \tag{I.4}$$

Then, the submatrices $X'X$ and $X'y$ are computed on the whole of the sample. Then the de-meaned matrix F is generated only over the movers. Effectively, to run the estimation only the non-zero columns are included (of dimension $T_i \times s$ for seller i with s buyers. So $F_s'X$ and its transpose and $F_s'y$ are computed and the system is solved for β and ψ.

To obtain the seller effects (I have labeled the outcome variable, i.e. the prices, as y to keep it consistent with the notation in the literature):

$$\hat{\theta}_i = \overline{y_i} - \overline{\hat{\psi}_i} - \overline{x_i}\hat{\beta} \tag{I.5}$$

where $\overline{\hat{\psi}_i}$ averages $\hat{\psi}_{j_i}$ over t and all the relevant j's.

The fixed effect for the seller contains both effects of time invariant observable characteristics of the seller and its unobserved heterogeneity. Assume this is decomposed in:

$$\theta_i = \alpha_i + u_i \nu \tag{I.6}$$

where α_i is the unobservable component and u_i is a vector of time invariant firm characteristics. In Abowd et al. (1999) it is shown that regressing $\hat{\theta}_i$ on u_i one can obtain consistent estimates of ν. Then α_i can be recovered as the difference between $\hat{\theta}_i$ and the linear fit from that auxiliary regression.

Appendix J

Qualitative Characterisation of Large Buyers: Factsheets

TABLE J.1: H&M

Name of the Firm	**Hennes & Mauritz AB (H&M)**
Description	(A) Swedish multinational retail-clothing company; (B) Known for fast-fashion clothing for men, women, teenagers and children
Parent Company	H&M
Description of Parent Company	Not applicable
Year of Creation	1947
Country of Origin	Sweden
Founder	Erling Persson
Relevant M&A	(A) Erling Persson opened Hennes in 1947; (B) Acquired Mauritz Widforrs, a hunting apparel retailer, in 1968, hence the name Hennes & Mauritz (H&M).
Main Products	(A) Women; (B) Men; (C) Kids; (D) Divided; (E) Denim; (F) Underwear; (G) Sportswear
Main Brand	(A) H&M; (B) COS; (C) Monki; (D) Weekday; (E) Cheap Monday; (F) & Other Stories
Yearly Sales (Overall)	(A) USD 23.03 billion (incl. VAT) in 2013; (B) USD 19.74 billion (excl. VAT) in 2013
Yearly Sales (Garment)	Income mainly generated from sale of clothing and cosmetics to consumers
Markets	(A) Asia Pacific; (B) Middle East and North Africa; (C) North and South America; (D) Europe
Market Share by Country/Region	(A) Germany (20%); (B) U.S.A. (10%); (C) France (7%); (D) UK (7%); (E) Sweden (5%) of sales
Relationship with Bangladesh Suppliers	(A) Accord on Fire and Building Safety in Bangladesh in 2013; (B) Skills training centers for helpers and fresh people in 1999
Source	H&M History; H&M Regions; H&M Report; H&M Products; Oanda Exchange Rate

TABLE J.2: Asda

Name of the Firm	**Asda Stores Ltd. (Asda)**
Description	(A) British supermarket chain which retails food, clothing, general merchandise, toys and financial services; (B) Uses the slogan "Britain's Lowest Priced Supermarket" to promote itself
Parent Company	Wal-Mart Stores, Inc.
Description of Parent Company	(A) Known as Walmart, Wal-Mart Stores, Inc. is an American multinational retail corporation; (B) Founded by Sam Walton on 1962 in U.S; (C) Owned and controlled by the Walton Family
Year of Creation	1949
Country of Origin	United Kingdom
Founder	Yorkshire Farmers
Relevant M&A	(A) Associated Dairies and Asquiths dealed and created Asda Stores Ltd., where two names of party, Asquith and Dairies, were combined; (B) George Davies Partnership (George Clothing) was introduced into Asda stores in 1989; (C) Waltermart acquired Asda in 1999; (D) Asda George Clothing was named after George Davies, founder of Next
Main Products	(A) Blazers Coats and Jackets; (B) Dresses and Jeans; (C) Jumpers and Cardigans; (D) Jumpsuits and Playsuits (E) Lingerie; (F) Maternity; (G) Nightwear; (H) Onesies; (I) Polo Shirt; (J) Shirts and Blouses; (K) Skirts; (L) Socks and Tights; (M) Swimwear; (N) Tops; (O)Trousers and Shorts; (P) Sweatshirts and Hoodies; (Q) Ties and Underwear
Main Brand	George Clothing
Yearly Sales (Overall)	(A) USD 26.8 billion in 2006; (B) USD 26 billion in 2005; (C) USD 21.7 billion in 2004
Yearly Sales (Garment)	USD 3.19 billion in 2005
Markets	United Kingdom
Rank in UK	Mintel Group Ltd., a London-based market research firm, estimates George clothing as the fourth largest retailer of clothing in UK after Marks and Spencer, Arcadia Group, and Next
Relationship with Bangladesh Suppliers	(A) George Clothing came up and comitted to a project called Lean Manufacturing to in increase factory productivity, improve worker skills and quality; (B) Works with Bangladeshi NGO's such as Phulki that promotes the rights of women and children and HERproject that promotes the health and empowerment of 20000 female workers; (C) George Clothing opened office in Bangladesh on 2010 to further develop their relationship with factory owners and workers and NGO's
Source	Asda History; Walmart History; Asda Report; Walmart Report; Walmart Report; Relationship with Bangladesh

Table J.3: Walmart

Name of the Firm	**Wal-Mart Stores, Inc. (Walmart)**
Description	(A) American multinational retail corporation; (B) Owned and controlled by Walton Family; (C) Operates in 27 countires under a total of 55 different names; (D) Officially incorporated as Wal-Mart Stores, Inc.
Parent Company	Wal-Mart Stores, Inc.
Description of Parent Company	Not Applicable
Year of Creation	1962
Country of Origin	U.S.A
Founder	Sam Walton
Relevant M&A	(A) Sam Walton purchased a branch of Ben Franklin Stores from the Butler Brothers in 1945; (B) Publicly listed in 1970; (C) Acquired Asda, a british supermarket chain, in 1999; (D) Sam Walton opened the first Sam's Club in 1983; (E) Acquired a majority of interest in Seiyu, one of the largest supermarket chains in Japan, which became a wholly-owned subsidiary of Walmart in 2008; (F) Walmart in Mexico acquired a majority position in Cifra in 1997 and changed the name to Walmart de Mexico (Walmex) 3 years after
Main Products	(A) Baby and Toddler; (B) Boys; (C) Girls; (D) Intimates and Loungewares; (E) Juniors and Juniors Plus; (F) Maternity; (G) Men's; (H) Big and Tall; (I) Women's and Wonen's Plus; (J) Young Men's
Main Brand	(A) Asda; (B) Sam's Club; (C) Seiyu Group; (D) Walmex
Yearly Sales (Overall)	(A) USD 466.11 billion net sales in 2013; (B) USD 443.85 billion net sales in 2012
Yearly Sales (Garment)	USD 31.07 billion or 7 % of net sales in 2012
Markets	(A) Africa; (B) Agentina; (C) Brazil; (D) Canada; (E) Central America; (F) Chile; (G) China; (H) India; (I) Japan; (J) Mexico; (K) United Kingdom
Market Share in US and International	(A) Walmart U.S. (58%) in 2013; (B) Walmart International (29%) in 2013; (C) Sam's Club (12%) of sales in 2013
Relationship with Bangladesh Suppliers	(A) Encourages Bangladesh government to review the minimum wages for wokers in garment industry by joining other leading brands and retailers; (B) Organises supply chain meeting focused on fire safety, conducting fire drills, and fire safety training; (C) Launched The Alliance for Bangladesh Worker Safety in coalition with North American retailers
Source	Walmart History; Walmart Countries of Operation; Walmart Garment Products; Walmart Report; Relationship with Bangladesh; ABC News

Table J.4: Gap

Name of the Firm	**The Gap, Inc. (Gap)**
Description	(A) American multinational clothing and accessories retailer; (B) Operates six primary divisions, namely Gap, Banana Republic, Old Navy, Piperlime, Intermix, and Athleta
Parent Company	The Gap, Inc.
Description of Parent Company	Not Applicable
Year of Creation	1969
Country of Origin	U.S.A.
Founder	Donald Fisher and Doris F. Fisher
Relevant M&A	(A) San Francisco-based Gap Inc. brought Banana Republic into the Gap Inc. Family in 1983; (B) Athleta was founded in 1998 and acquired by Gap Inc. on 2008; (C) Intermix was founded in 1993 and was acquired by Gap Inc. on 2012
Main Products	(A) Men; (B) Women and Women Plus; (C) Maternity; (D) Girls; (E) Boys; (F) Toddler Girls and Boys; (G) Baby Girls and Boys; (H) Petites; (I) Athletes
Main Brand	(A) Gap; (B) Banana Republic; (C) Old Navy; (D) Piperlime; (E) Intermix; (F) Athleta
Yearly Sales (Overall)	(A) USD 16.15 billion in 2013; (B) USD 15.65 billion in 2012; (C) USD 14.55 billion in 2011
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) Asia; (B) America; (C) Europe; (D) Africa; (E) Middle East
Market Share by Country/Region	(A) U.S.A. (78%); (B) Canada (7%); (C) Europe (5%); (D) Asia (9%); (E) Others (1%) of sales in 2013
Relationship with Bangladesh Suppliers	Provided help to Bangladesh garment workers in keeping the factories protected through fire and safety plan called the The Alliance for Bangladesh Worker Safety
Source	Gap History; Gap Inc. Report; Relationship with Bangladesh; Oanda Exchange Rate

Table J.5: Levis

Name of the Firm	**Levi Strauss & Co. (Levi's)**
Description	(A) Privately held American clothing company known worldwide for its Levi's brand of denim jeans; (B) Founded in 1853 when Levi Strauss came from Buttenheim, Bavaria to San Francisco, California to open a west coast branch of his brothers' New York dry goods business; (C) Corporate headquarters located at Levi's Plaza in San Francisco; (B) Made the first pair of Levis 501 jeans in 1890s
Parent Company	Levi Strauss & Co.
Description of Parent Company	Not Applicable
Year of Creation	1853
Country of Origin	U.S.A
Founder	Levi Strauss
Relevant M&A	(A) Expanded by adding new fashions and models, including stoned washed jeans, through the acquisition of a Canadian clothing manufacturere, the Great Western Garment Co. (GWG) in 1972; (B) Expanded from 16 plants to more than 63 plants in the United States and 23 overseas in just over the decade from 1964 to 1974; (C) Launched the Dockers brand in 1986, largely sold through department store chains in the United States; (D) Introduced Dockers into Europe in 1996; (E) Partnered with Filson, an outdoor goods manufacturer in Seattle, in 2010 to produce a high-end line of jackets and workwear
Main Products	(A) Jeans; (B) Pants; (C) Shorts; (D) Shirt Top; (E) Outerwear; (F) Jackets and Vests; (G) Dresses and Skirts
Main Brand	(A) Levi's; (B) Dockers; (C) Signature; (D) Denizen
Yearly Sales (Overall)	(A) USD 4.68 billion in 2013; (B) USD 4.61 billion in 2012; (C) USD 4.76 billion in 2011
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) America; (B) Europe; (C) Asia; (D) Middle East; (E) Africa
Market Share by Region	(A) Americas (61%); (B) Europe (24%); (C) Asia Pacific (2%) of sales in 2013
Relationship with Bangladesh Suppliers	Maintains relationship with 13 factory suppliers of garment from Bangladesh as of 2014
Source	Levis; Levis History; Levis Products; Levis Report; List of Suppliers

Table J.6: Next

Name of the Firm	**Next Plc (Next)**
Description	(A) British multinational clothing, footwear and home products retailer; (B) Headquarts located in Enderby, Leicestershire; (C) Operates around 700 stores, 597 in the UK and Ireland and around 200 are in continental Europe, Asia and the Middle East; (D) The largest clothing retailer by sales in the UK, having overtaken Marks & Spencer in early 2012 and 2014
Parent Company	Next Plc
Description of Parent Company	Not Applicable
Year of Creation	1864
Country of Origin	United Kingdom
Founder	Joseph Hepworth
Relevant M&A	(A) Hepworth & Son acquired Kendall & Sons Ltd, a Leicester-based rainwear and ladies fashion company from Combined English Stores in 1982 in order to redevelop the Kendall's stores as a womenswear chain of shops. Terence Conran, the designer, was Chairman of Hepworth's at this time and he recruited George Davies, who went on to become Chief Executive of Next; (B) Acquired Combined English Stores and the Grattan catalogue company in 1987; (C) Introduced Next childrenswear and the Next Directory in 1987 and 1988 respectively; (D) Sold 433 jewellery stores in the United Kingdom, which principally traded under the Salisburys and Zales brands, to the Ratners Group for USD232 million in October 1988; (E) Bought the youth brand Lipsy in 2008; (F) Launched an online catalogue for the United States in 2009 offering clothing, shoes, and accessories for women, men and children
Main Products	(A) Coats and Jackets; (B) Dresses; (C) Jeans; (D) Knitwear; (E) Lingerie; (F) Skirts; (G) Sportswear; (H) Swim and Beachwear; (I) Tops, Tshirts, Polos and Blouses; (J) Trousers and Leggings; (K) Underwear; (L) Sweat Tops and Hoodies
Main Brand	(A) Next Retail; (B) Next Directory; (C) Next International
Yearly Sales (Overall)	(A) USD 3.13 billion (Next Retail); (B) USD 1.56 billion (Next Directory); (C) USD 4.69 billion (Next Brand) in 2013
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) United Kingdom; (B) Continental Europe; (C) Asia; (D) Middle East
Sales by Brand	(A) Next Retail (21%, representing 500 retail branches in UK and Ireland); (B) Next Directory (11%); (C) Next Brand (32%) of sales in 2013
Relationship with Bangladesh Suppliers	(A) Provides training for factory management and personnel; (B) Assists in strategic improvement of workers safety by re-aligning existing expertise; (C) Supports the development of industry, building and fire safety action plan
Source	Next Brands and Products; Next Report; Relationship with Bangladesh; Oanda Exchange Rate

Table J.7: Primark

Name of the Firm	**Primark**
Description	(A) An Irish clothing retailer, first opened by Arthur Ryan in June 1969 in Dublin under the name Penneys, operating in Austria, Belgium, France, Germany, Ireland, Portugal, Spain, the Netherlands, and the United Kingdom; (B) Main headquarters located in Dublin; (C) A subsidiary of international food, ingredients and retail group Associated British Foods; (D) Employs 48000 people
Parent Company	Associated British Foods
Description of Parent Company	(A) ABF a diversified group of businesses grouped into five business segments, namely sugar, agriculture, retail, grocery, and ingredients; (B) A diversified international food, ingredients and retail group with sales of £13.3bn and over 113,000 employees in 47 countries
Year of Creation	1969
Country of Origin	Ireland
Founder	Arthur Ryan
Relevant M&A	(A) Opened first store in Dublin, Ireland in 1969; (B) Purchased the Littlewoods chain in 2005; (C) Opened first concession model in 2011 to include stocks in Selfridges department stores
Main Products	(A) Coats and Jackets; (B) Dresses; (C) Jeans; (D) Knitwear; (E) Lingerie; (F) Skirts; (G) Sportswear; (H) Swim and Beachwear; (I) Tops, Tshirts, Polos and Blouses; (J) Trousers and Leggings; (K) Underwear; (L) Sweat Tops and Hoodies
Main Brand	(A) Early Days; (B) Rebel; (C) YD; (D) Atmosphere; (E) Ocean Club; (F) Love to Lounge; (G) Opia; (H) No Secret; (I) Denim Co.; (J) Secret Possessions; (K) Cedar Wood State
Yearly Sales (Overall)	USD 6.26 billion revenue in 2013
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) United Kingdom; (B) Spain; (C) Ireland; (D) Germany; (E) Portugal; (F) Netherlands; (G) France; (H) Austria; (I) Belgium
Market Share by Country/Region	(A) UK (63%); (B) Iberia (16%); (C) Ireland (15%); (D) Northern Continental Europe (7%) of total stores in 2013
Relationship with Bangladesh Suppliers	(A) Provides financial support to the workers and families who were working in the factory that produced garments for Primark; (B) Accord on Fire and Building Safety in Bangladesh in 2013
Source	Primark History, Products and Brands; Associated British Foods; ABF Report; Relationship with Bangladesh; Oanda Exchange Rate

Table J.8: Tesco

Name of the Firm	**Tesco**
Description	(A) A multinational grocery and general merchandise retailer; (B) Headquart located in Cheshunt, Hertfordshire, England, United Kingdom; (C) The second-largest retailer in the world after Walmart, as measured by profits and revenues; (D) Operates stores in 12 countries across Asia, Europe, and North America; (E) The grocery market leader in the UK, Ireland, Malaysia, and Thailand; (F) Clothing brands include Cherokee, Stone Bay, True, and F+F (formerly Florence for women and Fred for men)
Parent Company	Teso PLC
Description of Parent Company	Not Apllicable
Year of Creation	1919
Country of Origin	England
Founder	Jack Cohen
Relevant M&A	(A) Founded in 1919 by Jack Cohen as a group of market stalls; (B) Purchased 70 Williamson's stores in 1957, 200 Harrow Stores outlets in 1959, 212 Irwins stores in 1960, winning the deal against Express Dairies' Premier Supermarkets, 97 Charles Phillips stores in 1964, and the Victor Value chain in 1968 which was sold to Bejam in 1986; (C) Completed the takeover of the Hillards chain of 40 supermarkets in the North of England in May 1987 for £220 million; (D) Took over the supermarket chain William Low in 1994, beating Sainsbury's for control of the Dundee-based firm, which operated 57 stores; (E) Purchased the retail arm of Associated British Foods in 1997, consisting of the Quinnsworth, Stewarts and Crazy Prices chains in the Ireland and Northern Ireland, and its associated businesses, for £640 million; (F) Formed a business alliance with Esso, a part of Exxonmobil, including several petrol filling stations on lease from Esso in 1997; (G) Signed a franchise agreement with Trent Ltd, part of the Tata group, to supply Star Bazaar with exclusive access to our retail expertise in 2008
Main Products	(A) Coats and Jackets; (B) Dresses; (C) Jeans; (D) Knitwear; (E) Lingerie; (F) Shorts and Skirts; (G) Sportswear; (H) Swim and Beachwear; (I) Tops, Tshirts, Polos and Blouses; (J) Trousers and Leggings; (K) Underwear and Nightwear; (L) Playsuits and Jumpsuits; (M) Socks and Tights; (N) Hoodies; (O) Komonos and Chinos; (P) Kids and Uniforms
Main Brand	(A) Cherokee; (B) F&F
Yearly Sales (Overall)	(A) USD 113.20 billion (sales inc. VAT) in 2013; (B) USD 100.23 billion (revenue exc. VAT) in 2013
Yearly Sales (Garment)	USD 29.43 billion (26% of sales are general merchandise, clothing, and electricals) in 2013
Markets	(A) United Kingdom; (B) Mainland China; (C) Czech Republic; (D) Hungary; (E) Republic of Ireland; (F) Japan; (G) Malaysia; (H) Poland; (I) Slovakia; (J) South Korea; (K) Thailand; (L) Turkey; (M) United States (N) India; (O) Kipa
Market Share by Country/Region	(A) United Kingdom (67%); (B) Asia (17%); (C) Europe (15%) of sales in 2013
Relationship with Bangladesh Suppliers	"(A) Provided support to factories to improve their people management, ethical leadership and new production techniques through the development by Tesco and the UK Government's Department for International Development (DfID) Responsible and Accountable Garment Sector (RAGS) of the Apparel Skills Foundation's Programme; (B) The pilot programme in May 2012 showed the following results: 19% increase in work per hour pay; 16% decrease in monthly working hours; 45% decrease in labour turnover; 25% decrease in absenteeism; 20% increase in the efficiency on the pilot line; (C) Participated in the pilot project for cleaner production of textiles in Bangladesh, together with other brands and retailers, resulting in the saving in 18 fabric mills of an annual equivalent of 300 million litres of water, 19000 tonnes of greenhouse gas emissions and GBP 520000"
Source	Tesco History; Tesco Products and Brands; Relationship with Bangladesh; Tesco Report; Oanda Exchange Rate

Table J.9: Phillips-Van Heusen (PVH Corp.)

Name of the Firm	**Phillips-Van Heusen (PVH Corp.)**
Description	(A) American leading dress shirt brand and top dress shirt brand synonymous with men's style; (B) Introduced the patented soft-folding collar in 1921, and has been associated with stylish, affordable shirts since then
Parent Company	Phillips-Van Heusen (PVH Corp.)
Description of Parent Company	(A) PVH Corp. an American clothing company owning brands such as Tommy Hilfiger, Calvin Klein, Van Heusen, IZOD, Arrow; (B) Owns licenses brands such as Geoffrey Beene, BCBG Max Azria, Chaps, Sean John, Kenneth Cole New York, JOE Joseph Abboud and MICHAEL Michael Kors
Year of Creation	1881
Country of Origin	Pennsylvania
Founder	Moses and Isaac Phillips
Relevant M&A	"(A) Incorporated in 1976 as a successor to the business begun in 1881; (B) D. Jones & Sons merged with Phillips in 1903; (C) Isaac Phillips met John Van Heusen, created their most popular line of shirts (Van Heusen) and renamed the corporation to Phillips-Van Heusen in the 1950s; (D) Received a patent for a self-folding collar in 1919 and released the product to the public in 1921; (E) Introduced the first collar-attached shirt in 1929 and the Bass Weejun in 1936; (F) Launched Geoffrey Beene shirts in 1982; (G) Acquired G.H. Bass in 1987, Izod brand in 1995, Arrow brand in 2000, Calvin Klein company in 2002, Superba, Inc. in 2007 (owning necktie licenses for brands such as Arrow, DKNY, Tommy Hilfiger, Nautica, Perry Ellis, Ted Baker, Michael Kors, Joseph Abboud, Original Penguin and Jones New York), and Tommy Hilfiger in 2010 (for 3 billion US dollars); (H) Began making men's clothing under the Timberland name in 2008, with women's clothing the following year; (I) Pulled Van Heusen brand out of European trading market due to losses in the third quarter of 2010 In November 2013 PVH sold the G.H. Bass brand and all of its assets, images and licenses to AM Retail Group"
Main Products	(A) Casual Shirts; (B) Dress Shirts; (C) Loungewear; (D) Neckwear; (E) Pants; (F) Sweaters; (G) Womens; (H) Big and Tall
Main Brand	(A) Calvin Klein; (B) Tommy Hilfiger; (C) Heritage Brands (Van Heusen, IZOD, Arrow, Speedo, Warner's, Olga); (D) Licensed Brands under Heritage Brands (Chaps, DKNY, Donald J. Trump, Geoffrey Beene, Kenneth Cole NY, Kenneth Cole Reaction, Michael Kors, SEANJOHN, Ted Baker London, Valentino Garavani)
Yearly Sales (Overall)	USD 8.22 billion in 2013
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) United States; (B) United Kingdom; (C) Australia; (D) Canda; (E) India
Market Share in North America and International	(A) North America (65%); (B) International (45% of which 20% Asia and Latin America)
Relationship with Bangladesh Suppliers	(A) Accord on Fire and Building Safety in Bangladesh, broadly inspecting factory and providing safety and training program in the garment industry, in 2013; (B) Participated in the Steering Committee of the Accord
Source	Van Heusen History; Phillips-Van Heusen (PVH Corp.) History; Van Heusen Products; Relationship with Bangladesh-Workers Rights Consortium; Relationship with Bangladesh; PVH Report;

Table J.10: VF Corporation

Name of the Firm	**VF Corporation**
Description	American clothing corporation selling jeanswear, underwear, daypacks, and workwear
Parent Company	VF Corporation
Description of Parent Company	Not Applicable
Year of Creation	1899
Country of Origin	Pennsylvania
Founder	John Barbey
Relevant M&A	(A) First established as Reading Glove and Mitten Manufacturing Company in Pennsylvania in October 1899 by John Barbey and others; (B) Started with a 320-square-foot factory leased for 60 US dollars per month and was incorporated in Pennsylvania in the same year; (C) Changed the name Vanity Fair Mills and manufactured undergarments in 1919; (D) Began selling shares to the public in 1951; (E) Acquired H.D. Lee Company (Lee Jeans) in 1969 and changed the corporate name to VF Corporation reflecting a more diverse product line; (F) Acquired Blue Bell Inc., owner of Wrangler and JanSport, in 1986, doubling the size of VF and making it the largest publicly held clothing company; (G) Sold the Lee brand jeans, in 2005 after parting ways with Fallon Worldwide in Minneapolis, part of the Publicis Groupe; (H) Sold the underwear business to Fruit of the Loom in 2007; (I) Acquired Majestic Athletic in 2007; (J) Purchased Seven for all Mankind and Lucy Activewear in 2007
Main Products	(A) Athletic and Sports Wear; (B) Jeans and Denims; (C) Women, Girls and Toddlers; (D) Pants and Shorts; (E) T-shirts
Main Brand	(A) Wrangler; (B) Lee Jeans; (C) Rustlers; (D) 7 For all Mankind; (E) 20X; (F) Chic; (G) Rock and Republic; (H) Ella Moss; (I) Bulwark; (J) Majestic; (K) Nautica; (L) The North Face; (M) Smartwool; (N) Red Kap; (O) Horace Small; (P) Splendid; (Q) Timberland; (R) Lucy Let's Go; (S) Nautica
Yearly Sales (Overall)	(A) USD 11.3 billion in 2013; (B) USD 10.77 billion in 2012
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) U.S.A.; (B) International (Western Europe, Japan, Eastern Europe, China, and South America)
Market Share in U.S.A. and International	(A) U.S.A. (62%); (B) International (38%) in 2013
Relationship with Bangladesh Suppliers	(A) Bangladesh Fire and Safety and Building Structure Plan in 2013; (B) Health and safety; (C) Training and capacity building; (D) Education and community development
Source	Van Heusen History; VF Corp Brands; Relationship with Bangladesh; VF Report; Oanda Exchange Rate

Table J.11: C&A

Name of the Firm	**C&A Europe (C&A)**
Description	(A) Dutch international chain of fashion retail clothing stores with branches in Austria, Belgium, Brazil, China, Croatia, Czech Republic, Denmark, France, Germany, Hungary, Italy, Luxembourg, Mexico, Netherlands, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Switzerland, Turkey; (B) European head offices in Vilvoorde, Belgium and Düsseldorf, Germany; (C) Part of the cityscape in many parts of Europe; (D) Named after the initials of names of its founders Clemens and August Brenninkmeijer
Parent Company	Cofra Holding AG
Description of Parent Company	(A) Cofra Group founded when the first C&A store was opened by brothers Clemens and August Brenninkmeijer in Sneek, Netherlands in 1841; (B) Established in 1911 in Zug, Switzerland specialising in retail, real estate, financial services, private equity and renewable energy; (C) Owns the international chain of clothing stores C&A; (D) Manages network of stores and online-shops in Europe, Brazil, Mexico, and China aiming to provide high quality and affordable fashion for the whole family
Year of Creation	1841
Country of Origin	Germany
Founder	Clemens and August Brenninkmeijer
Relevant M&A	(A) Managed to have an expansive network of stores and online-shops in Europe, Brazil, Mexico, and China; (B) Opened textile warehouse in Nethrelands in 1841; (C) Introduced standard sizes as well as the customer-friendly option to exchange goods; (D) Ventured in retail banking with its product C&A Money; (E) Closed last store in UK in 2001; (F) Withdrawn market in Argentina in 2009
Main Products	(A) Ladies; (B) Men; (C) Young Fashion; (D) Boys; (E) Girls; (F) Babies
Main Brand	(A) Yessica; (B) Yessica Pure; (C) Your Sixth Sense; (D) Angelo Litrico; (E) Westbury; (F) Canda; (G) Clockhouse; (H) Baby Club; (I) Palomino; (J) Here & There; (K) Rodeo Sport
Yearly Sales (Overall)	USD 9.47 billion total gross sales in 2011
Yearly Sales (Garment)	Income mainly generated from sale of clothing and accessories
Markets	(A) Europe; (B) Brazil; (C) Mexico; (D) China
Market Share by Country/Region	(A) Germany (45%); France (9%); (C) Iberian (8%); (D) Belgium and Luxemberg (8%); (E) Netherlands (7%); (F) Switzerland (7%); (G) Eastern Europe (7%); (H) Austria (6%); (I) New Markets, i.e., Croatia, Romania, Hungary, Italy, and Turkey (2%) of sales in 2011
Relationship with Bangladesh Suppliers	(A) Opened vocational training centre by Dutch ambassador in Dhaka; (B) Accord on Fire and Building Safety in 2013
Source	C&A History; C&A Products; Relationship with Bangladesh; Cofra Holding AG History; C&A Report; C&A Social Responsibility; Oanda Exchange Rate

Table J.12: Carrefour

Name of the Firm	**Carrefour S.A. (Carrefour)**
Description	(A) French multinational retailer headquartered in Boulogne Billancourt, France; (B) One of the largest hypermarket chains in the world with 1452 hypermarkets at the end of 2011, the fourth largest retail group in the world in terms of revenue after Wal-Mart, Tesco and Costco, and the third in profit after Wal-Mart and Tesco; (C) Operates mainly in Europe, Argentina, Brazil, China, Dominican Republic, United Arab Emirates, Qatar and Saudi Arabia; (D) Word carrefour means "crossroads" and "public square" in French
Parent Company	Carrefour S.A.
Description of Parent Company	Not Applicable
Year of Creation	1959
Country of Origin	France
Founder	Marcel Fournier, Denis Defforey and Jacques Defforey
Relevant M&A	Merged with Promodes, known as Continent, one of its major competitors in the French market in 1999
Main Products	(A) Women's; (B) Men's; (C) Children's
Main Brand	TEX
Yearly Sales (Overall)	USD 99.45 billion net sales in 2013
Yearly Sales (Garment)	Difficult to find information on sales of Tex, Carrefour's textile brand, but a range of the brand were introduced in French and Romanian stores in 2013.
Markets	(A) Asia; (B) Europe; (C) Middle East; (D) Africa; (E) Latin America;
Market Share by Country/Region	(A) France (47%); (B) Other Europe (26%); (C) Latin America (18%); (D) Asia (11%) of sales in 2013
Relationship with Bangladesh Suppliers	(A) Human Rights; (B) Fire and Building Safety Alliance
Source	Carrefour History; Carrefour Brands and Products; Relationship with Bangladesh-Human Rights; Relationship with Bangladesh-Fire and Building Safety Alliance; Relationship with Bangladesh-Fire and Building Safety Alliance; Carrefour Annual Report; Oanda Exchange Rate

Table J.13: Kmart

Name of the Firm	**Kmart Corporation (Kmart)**
Description	(A) American chain of discount department stores known for its Blue Light Specials, a promotion of discounted products in a specfic part of the store; (B) Headquarter in Illinois, United States; (C) Purchased Sears in 2005, forming a new corporation under the name Sears Holdings Corporation
Parent Company	Sears Holdings Corporation
Description of Parent Company	(A) Sears Holdings Corporation a leading integrated retailer focused on delivering digital and physical shopping experiences to its members; (B) Host of a social shopping platform Shop Your Way offering rewards for shopping at Sears and Kmart; (C) Operates through its subsidiaries Sears, Roebuck and Co. and Kmart Corporation with more than 2350 full-line and specialty retail stores in the United States and Canada.
Year of Creation	(A) 1899 founded S.S. Kresge; (B) 1977 renamed to Kmart Corporation
Country of Origin	U.S.A.
Founder	Sebastian S. Kresge
Relevant M&A	(A) Founded in 1899 and was incorporated in 1902 in Delaware; (B) Reincorporated in Michigan in 1916; (C) Founded Canadian subsidiary S.S. Kresge Ltd. in 1929; (D) Organized Kmart Australia Limited by S.S. Kresge and G.J. Coles and Coy Limited in 1968; (E) Moved headquarters from Detroit to Michigan; (F) Exchanged 51% interest in Kmart Australia Limited for 20% interest in G.J. Coles and Coy Limited in 1978 which increased to 21% in 1985, and was divested in 1994; (G) Acquired Walden Book Company and Home Centers of America in 1984; (H) Sold most U.S. Kresge and Jupiter stores to McCrory Corporation; (I) Purchased The Sports Authority in 1990; (J) Acquired 22% interest in OfficeMax in 1990, which increased to 90% a year after; (K) Acquired Borders, Inc. in 1992; (L) Purchased stores in Czech Republic and Slovakia in 1992 which was later sold in 1996; (M) Sold the operations of Builders Square and Kmart Canada; (N) Forged a long-term merchandising agreement with Martha Stewart Omnimedia, Inc. and with Fleming in 2001; (O) Acquired BlueLight.com, company's e-commerce subsidiary, in 2001; (P) Kmart Holding Corporation merged with Sears, Roeback and Co. in 2004
Main Products	(A) Women's; (B) Men's; (C) Children's
Main Brand	(A) Alphaline; (B) Bongo; (C) Canyon River Blues; (D) Covington; (E) Craftsman; (F) Dream Out Loud; (G) Jaclyn Smith; (H) Joe Baxer; (I) Land's End; (J) Latina Life; (K) Parallel; (L) Personal Indentity; (M) Route 66; (N) Sesame Street; (O) Structure; (P) Toughskins; (Q) Two Hearts; (R) Winnie the Pooh
Yearly Sales (Overall)	(A) USD 36.19 billion revenues in 2013 (Sears Holdings Corporation); (B) USD 13.19 billion revenues in 2013 (Kmart); (C) USD 19.20 billion revenues in 2013 (Saers Domestic); (D) USD 3.80 billion revenues in 2013 (Sears Canada)
Yearly Sales (Garment)	(A) USD 11.24 billion revenues (Sears Holdings Corporation); (B) USD 4.30 billion revenues in 2013 (Kmart); (C) USD 5.20 billion revenues in 2013; (D) USD 1.74 billion revenues in 2013 (Sears Canada)
Markets	(A) U.S.A.; (B) Purto Rico; (C) U.S. Virgin Islands; (D) Guam
Market Share by Country/Region	(A) U.S.A. (97%); (B) Puerto Rico (2%); (C) U.S. Virgin Islands (0.30%); (D) Guam (0.09%) of total stores in 2013
Relationship with Bangladesh Suppliers	(A) Safety and worker's rights; (B) Regular audits with regular suppliers
Source	Kmart History; Kmart Brands and Products; Sears Holdings Corp. History; Relationship with Bangladesh; Sears Holding Corp. Annual Report

Appendix K

Specific Contributions

This thesis was entirely written by its author. Specific contributions by Research Assistants to related projects are detailed below and the supporting evidence is available on request:

TABLE K.1: Contributions by Third Parties included in this Thesis

Contributor	Capacity	Frame	Contribution	My Role	Supporting Evidence
Ankira Patel	Undergraduate Research Assistant	Project - Prof. Macchiavello	Writing .do file that cleaned 'manually' strings with names of buyers, as detailed in Appendix B; improvement of an additional 5.5% over already cleaned data	Supervision of her tasks, jointly with Prof. Macchiavello	Email exchanges; log of hours
Celine Harion	External Research Assistant	CEPR Project - Prof. Woodruff	Writing .do file under my instructions to reproduce on the imports data the cleaning procedure of the import-export merging variable I had written for the exports data, as detailed in Appendix D	Supervision of her tasks, jointly with Prof. Woodruff	Email exchanges; .do files and .txt files
Jose Corpuz	Graduate Research Assistant	PEDL Grant (Julia Cajal Grossi) and Prof. Woodruff	Gathering and systematisation of data used in: figures C.1 to C.1; International Trade Costs (Appendix C); Tables in Section C.2.; Policy Review in Appendix E; Firms factsheets in Appendix J	Supervision of his tasks, jointly with Prof. Noguera	Email exchanges; .txt files and instruction files

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