# Essays in Development Economics

by


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# Declarations

The second chapter, *Farmer Bargaining Power & Relational Contracts in the Sugar Industry in Colonial Taiwan* and the fourth chapter *Product Customisation and Optimal Firm Size* are solely my own work. The third chapter, *The Benefits of the Bamboo Network in International Trade* has been coauthored with Anna Baiardi. We contributed in equal parts to the data preparation and development of the empirical strategy. The results and the interpretation were developed from joint discussion.

I declare that the material contained in this thesis has not been used or published before, and has not been submitted for another degree or at another university.

Christina Ammon

September 2016

# Abstract

This thesis is a collection of three essays studying firms in low income countries. The first chapter explores how relational contracts that substitute for formal contracts in the presence of weak institutions, are affected by changes to the outside option of one of the parties. I investigate this question by assessing how a change in the pay-off of cultivating an alternative crop by farmers affects the relationship with downstream buyers in the sugar industry in colonial Taiwan (1895-1945). Using novel historic sugar mill level data, I analyse effects on interlinked lending and the provision of inputs by mills to farmers following a reversal of the downward price trend of the main alternative crop, rice. In the second chapter, which is co-authored with Anna Baiardi, we empirically assess the importance of ethnic networks in facilitating international trade. In particular, we investigate the impact of ethnic Cantonese networks in the United States on the export performance of firms based in Southern China. In the third chapter, I investigate whether the dominance of small firms in developing countries can be explained by the production of customised goods, which allows smaller and less efficient firms to compete with larger and more efficient modern firms. I incorporate this hypothesis in a model, in which the key variables impacting the profitability of the customised technology and thus firm size are transport costs and income.

# Abbreviations

| | |
|---|---|
| ATE | Average Treatment Effect |
| FDI | Foreign Direct Investment |
| GAEZ | Global Agro-Ecological Zones |
| ISIC | International Standard Industrial Classification |
| IT | Information Technology |
| FAO | Food and Agriculture Organization of the United Nations |
| NAICS | North American Industry Classification System |
| NBER | National Bureau of Economic Research |
| OECD | Organisation for Economic Co-operation and Development |
| OLS | Ordinary Least Squares |
| R&D | Research and Development |
| RMB | Renminbi |
| TFP | Total Factor Productivity |
| TFPR | Total Factor Productivity Revenue |
| SIC | Standard Industrial Classification |
| U.K. | United Kingdom |
| U.S. | United States |
| ¥ | Japanese Yen |
| SD | Standard Deviation |

# Chapter 1

# Introduction

Why some countries are poorer than others is one of the most important questions in development economics. The current consensus seems to be that income differences cannot be explained purely by differences in capital and labour, but instead are accounted for to a large extent by differences in total factory productivity, or TFP (Caselli, 2005). At the same time, this difference in aggregate productivity is attributed in part at least to the misallocation of scarce resources. The idea is that market distortions are causing resources not to be allocated to the firms for which the marginal product is the highest (see for example Hsieh and Klenow (2007) or Restuccia and Rogerson (2013)). Therefore, the study of the constraints and distortions faced by firms in developing countries is key in understanding productivity and hence income differences. It is therefore unsurprising that this topic has sparked a vast literature which investigates how firms are affected by a numerous constraints and distortions in many different settings. The constraints and distortions highlighted by this literature range from credit constraints and distorting labour laws to weak institutions (Banerjee and Duflo, 2005, 2012). However, there is still not a clear consensus which factors are the most important in explaining misallocation. This thesis adds to this literature by studying a related question, namely what mechanisms firms and other agents develop in order to (partially) overcome the constraints and distortions they face.

In this vain, the first chapter focuses on the topic of relational contracts [1], which allow credit to be supplied despite of weak enforcement institutions. I study how sustainable these contracts are to changes of the outside option of one of the parties in the context of the sugar industry in colonial Taiwan. More specifically, I analyse how interlinked lending provided by mills to its suppliers - sugar cane farmers - is affected by a change in the outside option of a subset of the farmers. The outside option is affected by a change in the trend in the price of rice, the main alternative exportable crop. Due to the particular institutional environment, which allocates to each mill a specific fixed area from which it can source cane, I am able to implement a difference-in-difference strategy with a continuous treatment intensity according to the suitability of this area for rice cultivation. I digitalise novel historic data regarding lending, production as well as a number of mill level variables. The results indicate that the improvement in the outside option of farmers has a large and significant effect on lending: A one standard deviation increase in the suitability for rice is associated with a decrease of loans by up to 26%. These results have important policy implications as if these adjustments made by downstream buyers are not taken into account policies that strengthen the bargaining power of small-scale producer could have unanticipated negative effects.

The second chapter, on the other hand, analyses how firms are able to overcome informational and contractual barriers to exporting with the help of ethnic migrant networks in the destination country. More specifically, the chapter considers how firms in southern China that are located in counties that saw a large share of its population emigrate to the United States in the 19th century (referred to as *sending counties*), benefit from their closer relationship to the American-Chinese population. Access to the network is assumed to vary along two dimensions: Firms are assumed to have better access to the American-Chinese network if they are located in one of the original sending counties *and* are active in an industry that employs a larger number of ethnic Cantonese in the U.S. This interaction allows us to control for geographic and industry characteristics by including fixed effects. The results show that

[1] Relational contracts are defined as informal contracts that cannot be enforced through formal institutions, but are sustained by the value parties place on the overall relationship.

networks play an economically significant role in facilitating trade both through the extensive and intensive margin. In addition, we find supporting evidence that networks predominantly promote trade by lowering information barriers.

Finally, the third chapter investigates how firms respond to high transport costs by adopting technologies which allow different degrees of product customisations and in how far transport costs in this way can explain the fact that the firm size distribution in developing countries is skewed to the right. My hypothesis is that small firms are able to customise their goods by using a more flexible production technology, which is, however, associated with a higher marginal cost. Large firms, in contrast, use a more mechanised and cost-efficient technology, which limits them to producing a single variety. Finally, while standardised goods can be shipped across markets, the customised firms are only able to sell one specific location. This is key in explaining the size difference: customised firms are smaller due to higher marginal costs and due to being limited to a single location. I incorporate these assumptions into a spatial competition model with heterogeneous productivity. My model predicts that larger transport costs are associated with a larger number of small firms. Furthermore, income has a non-monotonic effect on the share of small firms. When incomes are below a threshold, increases will lead to a decrease in the share of small firms. However, as income rises further, the share of small firms increases again.

# Chapter 2

# Farmer Bargaining Power & Relational Contracts in the Sugar Industry in Colonial Taiwan

## 2.1 Introduction

Farmers in rural areas of developing countries often do not have access to formal financial institutions. Instead, they rely on other agents in the supply chain for credit, such as intermediary buyers of their products (Hoff and Stiglitz, 1990). Through sustaining relational contracts, these agents are thus able to supply credit profitably despite the weakness of formal contracting institutions. Relational contracts are contracts that are self-enforcing due to the value placed on continuing the relationship i.e. in order to be sustainable, the rents associated with long-term relationships need to be sufficiently large compared to the parties' outside option. For example, a buyer might be willing to supply credit as the threat of termination of the buyer-seller relationship, which is valued by the farmer, reduces the likelihood of default. Given the prevalence of such informal contracts and their importance for a possible supply of credit, understanding which factors determine the sustainability of these informal contracts is an important question in development (Deb and Suri, 2013).

This paper focuses on how a change in the outside option of sugar cane farmers affects the interactions with intermediary buyer i.e. sugar mills in Taiwan during the Japanese colonisation (1895-1945). In this setting, the outside option of a subset of sugar cane farmers is the cultivation of the main alternative cash-crop, rice. As there were few non-agricultural opportunities, a change in the pay-offs of rice cultivation is likely to be salient. Specifically, I investigate how the reversal in the trend of rice prices in mainland Japan affects sugar cane production through its impact on mill-to-farmer lending and provision of inputs (e.g. fertilisers and seeds).

Rice prices could affect the sustainability of relational contracts in the following way: Consider for example an increase in rice prices. This increase lessens the relative rents associated with maintaining a relationship with sugar mills for the relevant subset of sugar cane farmers. Therefore, the termination such relationships becomes less severe and as such farmers have a greater incentive to default on loans provided by mills. In anticipation, mills will reduce the amount of credit they supply. This reduction in the supply of credit, however, reduces overall farmer welfare. The mechanism described here is similar to the effect highlighted in Macchiavello et al. (2015), who investigate the effect of competition between downstream buyers on relational contracts, which is seen to be significant and negative.

In general, the challenges encountered within the empirical study of factors affecting the sustainability of relational contracts are twofold as not only credible measures of relational contracts have to be recorded, but also exogenous variation in the factors have to be identified. As such, this setting lends itself to studying the effect for a number of reasons. Focusing on only one specific industry allows for the identification of credible measures of relational contract practises. More importantly, the particular cultivation environment required by rice and sugar allow me to implement a difference-in-difference strategy with continuous treatment intensity, where the suitability for rice cultivation determines the intensity of treatment by the change in rice prices.

More specifically, the identification strategy relies on the specificity of the contracting environment of the sugar industry in colonial Taiwan: In order to better align the incentives of farmers and mills, in 1905 the Japanese administration passed a law which allocated to each mill an exclusive "command" area, i.e. an area within which all farmers were only allowed to sell sugarcane to the respective mill. In return, mills committed to purchase all sugarcane grown at a previously announced price. Figure (2.4) shows a map of all command areas in 1918. The command areas were fixed over time and new mills' areas were restricted to land that was not within the command area of another mill. Thus the area from which sugar mills could source cane from was fixed over time. It is important to note that these policies are common across the developing world and is not restricted to sugar cane.

At the same time, fields in Taiwan could be roughly divided into two types: paddy (or wet) fields, which can be sufficiently flooded to grow rice and dry fields with insufficient irrigation for growing rice. Sugarcane however, can be grown both on paddy and dry fields, due to lower irrigation needs.

As the price of rice increased, the outside option of farmers that farmed paddy fields increased, while it remained unchanged for farmers with dry fields. Therefore, keeping the share of paddy fields in each mills catchment area fixed at their 1918 level, I implement the difference-in-difference strategy with continuous treatment intensity according to the field composition of the catchment areas and using both the *change in trends* of rice prices as well as year on year variation. The identifying assumption is that mills with different shares of paddy fields would have experienced the same time-trend in the absence of treatment.

The information about mill and farmer performance is taken from the *Taiwan Togyo Tokei* (1913-1944) (Taiwan Sugar Statistics), which records yearly statistics about the universe of modern sugar mills during the second half of the colonial period. I digitalise the data for the period of 1929-1939. To my knowledge, I am the first to have digitalised and translated the data to this degree of detail. The main outcomes of interest are measures of relational contracts such as lending and provision of inputs by mills to farmers. I further collect data on other farmer and mill outcomes, such as area cultivated with sugarcane, yields, fertiliser use, and information about manufacturing activities.

The results found in this paper indicate that the permanent change in rice prices had a significant effect on mill-farmer lending: A one standard deviation increase in the share of paddy fields of the total area suitable for cane cultivation is associated with an up to 26% decrease in fungible loans provided by the mills. On the other hand, I find that the provision of non-fungible inputs remains unchanged. Short run price changes seem to have the opposite effects: a short-run price increase has no effect on monetary lending but increases the inputs provided, which could be indicative of improvements of farmer bargaining position. The result is robust to the inclusion of various control variables as well as prefecture-year fixed effects and mill-level linear trends. I also find no evidence that would lead me to reject the parallel trends assumption.

Further I investigate how other decisions by farmers and mills are affected. I find that the overall area cultivated with sugarcane remains nearly unchanged, though the composition changes. The share of paddy fields is reduced, while the share of dry-fields increases. In addition, I find that though fertiliser usage remains stable, yields are reduced significantly, by nearly 8% overall and by up to 14% for paddy fields. This could be indicative of both adverse incentive effects for farmers but also changes to the field composition. Concerning mill behaviour, I find very little changes except for an increase in the days of inactivity of mills caused possibly by mis-coordination in the harvesting process, which might be indicative of a further breakdown of the mill-farmer relationship.

The closest related paper is Macchiavello et al. (2015), who analyse the effect of competition on the sustainability of relational contracts in the Rwandan coffee industry. Here, the outside option of farmers is affected through variations in their ability to sell to other mills with which they do not have a relationship. The authors instrument the location of coffee processing mills using geographic characteristics as inputs to an engineering model that predicts the best location of mills. They then investigate how this arguably exogenous variation in competitiveness of the environment of a given mill affects the relational contract between mills and farmers. They find greater competition leads to a deterioration of relational contract practises, which are at the same time associated with a negative effect on mill efficiency, capacity utilisation and quality of coffee produced. This in turn seems to constrain farmers' access to credit and inputs, which is likely to reduce farmers' well-being. In contrast to this paper, however, Macchiavello et al. (2015) rely on cross-sectional data, which does not allow for the analysis of dynamic changes to the outside options of farmers. Thus, the main addition of this paper is in allowing the dynamic study of how much and how fast existing informal contracts are affected.

This paper proceeds as follows. Section 2.2 gives historic and contextual background on the Taiwanese sugar industry and Japanese rice policies. Section 2.3 gives a description of the data and section 2.4 outlines the empirical strategy. The results are presented in, section 2.5 and in section 2.6. Finally, section 2.8 concludes.

## 2.2 Background & Variation in Exposure

### 2.2.1 The Sugar Industry in Colonial Taiwan

#### Japanese Colonisation

Previous to Japanese colonisation, Taiwan had been colonised already by both the Spanish and the Dutch in the 17th century, though both nations only controlled a small share of the total territory. Eventually it officially came under Chinese control in 1683 and gained prefecture status in 1887. At the time, Taiwan was characterised by its under-development and lack of rule of law relative to mainland China. After the first Sino-Japanese War in 1895, Taiwan was seceded to Japan under the Ma Kuan Treaty and became a Japanese colony until 1945, when Japan surrendered unconditionally. The first years of the Japanese colonisation were characterised by fierce resistance by the Taiwanese population against the coloniser and thus Japanese policy was focused on controlling the island. After 1915, however, conflicts had essentially ended. The Japanese government then invested heavily in the modernisation of the island including infrastructure, sanitation and schooling (Chou et al., 2007).

Before the Japanese colonisation, agriculture, with the exception of tea and sugar, was either subsistence crops or focused on domestic consumption. Figure A.1 shows the distribution of production in 1905, ten years after the begin of the Japanese colonisation, but before any modernisation interventions had taken place. While both rice and sugarcane were grown before the arrival of the Japanese, the production was characterised by a low degree of mechanisation. Both rice and sugar were therefore also imported in certain years.

Sugarcane was the main cash crop and export good in colonial Taiwan. Sugar had been produced in Taiwan since the 16th century, with the knowledge having been brought by immigrants from mainland China. However, both the agricultural as well as the industrial technology remained essentially unchanged until the arrival of the Japanese colonialists, which invested heavily to modernise the industry. The traditional production technique was characterised by low yields, high labour intensity and the production of low quality product. While some larger mills existed, which were able to produce white sugar, the majority of mills were very small and produced brown sugar for domestic consumption. Before the arrival of the Japanese colonisers, Taiwan was thus far behind the world frontier: while Java and Hawaii, the most productive sugar producers in the 19th century, produced 30-34 tons of cane per acre, Taiwan produced merely 12 (Davidson, 1903). Even before colonisation, the main export destination for sugar was Japan. Farmers operated under share-cropping agreements and were able to obtain limited loans from sugar merchants. Even under this system farmers were supposed to sell their cane to their lender, however, there was free competition between lenders and there was no formal enforcement mechanism of this rule. Hence, unsurprisingly, defaults were common, leading to credit rationing and high interest rates (**?**).

Modernising the sugar industry was one of the main objectives of the Japanese government with the aim of increasing production and thus reducing Japan's reliance on imports. The key areas for improvements were the planting of high-yielding cane varieties and the increased use of fertiliser, the construction of irrigation systems and the manufacturing of sugar in so called modern mills, which use modern machinery, such as steel crushers and vacuum pans (Shih and Yen, 2009). While the Japanese administration invested in irrigation and developed improved seeds suitable for the cultivation in Taiwan, one of the key steps was the passing of the *Sugar Industry Incentive Regulations* in 1905. In order to decrease hold-up problems and increase the incentives for the sugar mills to invest in improving cane cultivation, mills were allocated exclusive procurement or command areas within this regulation. This implied that farmers within a mill's command area were only allowed to sell to that specific mill. Further farmers were not allowed to transport cane across Prefecture borders. On the other hand, mills had to announce a purchasing price for the cane before planting took place, i.e. around one and a half years before harvests. These prices were recorded centrally and published in an industry publication. Mills then had to commit to purchase all cane produced within their command area for the announced price (Ka, 1991). In order to ensure sufficient supplies, mills were providing fertiliser, seeds and other loans. The interest rate for these loans had to be announced at the same time with cane prices before the first planting i.e. 18 months in advance and published centrally, making it easier for farmers to enforce prices. Mills however were allowed to and did often price discriminate and charged differentially for paddy and dry fields, but also paid higher prices per ton to farmers with more productive fields (Koo and Wang, 1999).

Under these measures, the sugar industry developed successfully. By 1910, 29 modern mills had been founded, a number that rose to 45 by 1939. With the outbreak of World War II, the sugar industry became strategically important, as one of the side products of sugar production, molasses, could be used for ethanol production, which in turn was used to power various war machinery. Thus the industry became much more regulated and production targets were set centrally.

### 2.2.2 Sugar Production

All sugar production follows the same basic principle: sugarcane is first crushed, and a sucrose-rich juice is extracted. Afterwards the juice is cleansed of impurities, then reduced through boiling and finally the molasses are separated from the sugar crystals. However, each step of the process can be mechanised to a differential degree. Mechanisation, such as mechanical cutters, vacuum pans and centrifuges, does not only lower marginal costs, but equally importantly increases the quality of sugar.

An important managerial aspect is the timing and coordination of harvest, as sugarcane needs to be processed within hours of harvesting. On the one hand, the large cutters functioned best when a certain amount of sugar is being processed at any given time. On the other hand of course maximum capacity constrains the amount of sugar that could be processed at any given time. In addition, preventing machine breakdowns and organising swift repairs can influence efficiency significantly, as otherwise the cane at the mill will start to deteriorate. For a more detailed discussion of sugar production see Sukhtankar (2016).

The growing period of sugar varies according to the climate it is grown in: in the tropical south of Taiwan, the growth period is around one year, while it averaged around 18 months in the sub-tropic north. The crop is water- and fertiliser intensive, however in Colonial Taiwan it was traditionally mostly rain-fed. Fertiliser, which was previously rarely used, as well as new seed varieties were subsidised by the Japanese Governor General. The harvesting period in Taiwan started between December and continued until May. In the tropical south in principle cane can be grown during the entire year; however, possibly due to irrigation needs, this was not done during the period. The quality of cane is predominantly defined by its sucrose content, which causes mills and farmers to have opposing incentives regarding the optimal harvesting period: While later harvesting leads to a higher sucrose content, it also implies lighter and dryer cane. Since prices are paid to the farmer per ton of cane, drier cane implies a lower income to the farmer (Koo and Wang, 1999).

### 2.2.3 Rice Cultivation and Agricultural Rice Policy in Japan

Japanese rice prices experienced a period of extreme volatility from 1910-1940, which is characterised by a number of trends caused by economic policy interventions into the rice market in Japan.

During the 1910s rice prices were rising rapidly. Bad harvests in 1918 caused the price to peak further, which lead to widespread riots by urban workers. To respond to the rising prices, the Japanese government focused on expanding rice production both in Japan as well as in the colonies, Korea and Taiwan. Previously, Taiwan had not exported any rice to Japan as the rice varieties produced in Taiwan did not suit Japanese tastes and were used only for domestic consumption. On the other hand, rice varieties planted in Japan were not suitable for the tropical climate of Taiwan. Thus, in order to start importing rice from Taiwan, the Japanese needed to develop new rice varieties, which succeeded in 1925. Similar schemes were under way in Korea, which was the dominant source of rice for the Japanese market.

Due to the expansion in the rice production capacity from the 1920s onwards, the rice price started to decrease dramatically form 1925. This was partly due to the increased production in the colonies, particularly in Korea, but also in Taiwan. However, domestic production had also increased significantly. Coupled with the economic recession after 1929, the overproduction lead to collapse of prices. In 1930, the price of rice fell by up to 30%, leading to unrest of rice farmers in Japan. The Japanese government responded through several measures between 1931 and 1933. In 1931, a revision of the rice law was passed, which stated that the state would put upper and lower bounds on the price of rice and further subsidised rice storage. Furthermore, in 1932 the government quite suddenly committed to unlimited rice purchases, and further expanded the purchasing schemes in 1933. At the same time, with the military actions in Manchuria in 1931, the demand for rice increased independently (Sheingate, 2003). As a result the trend of rice prices was reversed and prices continued to increase until the outbreak of World War II.

[] Overall, the Japanese rice prices followed rice prices in most South-East Asian countries until the early 1920s, when all countries experienced a spike in their prices. However, the Japanese reaction to the price spike of aggressively increasing production, changed the price trajectory in the Japanese market. While Japanese prices started to decrease dramatically from 1925 onwards, most other countries in the region experienced a continuous increase in prices until 1930. This increase however, was reversed dramatically in 1931 when rice prices in many countries nearly halved. This was due to the Depression in general, as well as protectionist policies among others in Japan in particular. Japan was one of the largest markets and importers of rice in the 1920s and therefore the trade restrictions heavily affected rice prices in its neighbouring countries. Table A.2 shows the prices for the example of Thailand. Prices in the region slightly recovered until the end of the 1930s, however never came close to the 1920 levels (Boomgaard and Brown, 2000).

Clearly, Japanese rice prices experienced a very different trajectories than those of most nations in the region. This can be explained by the heavy protectionism Japan imposed as well as the aggressive interventions in the rice market. Rice prices fell earlier than in most other countries due to the development of overproduction in Japan and its colonies, and were increasing and not falling in the 1930s due to the extensive purchasing scheme imposed by the government, which purchased sufficient rice to positively affect prices. []

## 2.3 Data and Descriptive Statistics

In this section, I give a brief overview of the most important datasets and the main variables of interest as well as some summary statistics.

### 2.3.1 Outcome Variables

#### Data on Lending and Input Provision

The data on lending and the provision of inputs by mills to farmers is digitalised from the *Taiwan Togyo Tokei* (1913-1944) (referred to as Taiwan Sugar Statistics). The data was self-reported by the factories and published annually at the mill level. The Taiwan Sugar Statistics was published by the Governor Generals Office from 1913 until 1944. Information on lending and similar activities, however, only becomes available from 1929 onwards. Furthermore, I exclude data after the outbreak of World War II, as not only did the Japanese intervene more forcefully in the market during this period, but also sugar factories were targeted by allied bombing during the later stages of the war. Thus, I focus on the period of 1929 to 1939.

The Japanese administration recorded information on three different types of mills: so called *traditional mills*, which received no subsidies and which did not have to register, so called *improved mills*, which were Taiwanese owned mills and which received subsides for capital investment but in return had to register and supply a limited amount of data and finally the so called *modern mills*, which were registered, listed, received significant subsidies and had to publish detailed data on a yearly basis, which includes the information on lending. In the analysis I focus exclusively on the modern mills.

As mills are identified by name, I am able to construct an unbalanced panel of 45 modern mills. As the the empirical strategy applied requires that firms exist already in 1918. This leaves me with 35 mills that were founded before 1918 and exist until 1939. Table A.3 lists all of the modern mills active over our period of interest and whether the firm is in our sample, as well as its ownership, age, capacity and share of paddy fields of the total catchment area.

Loans are recorded in Japanese Yen and include both loans made for working capital as well as miscellaneous (consumption) loans. Furthermore, loans made in kind for inputs are also recorded in Yen value and include the provision of fertiliser and seeds. One outcome variable is the log total value of loans by type provided. However, a decrease in the total value of loans provided could not only be caused by a decrease of supply by the mills due to the decreased willingness to lend, but it could derease mechanically if the area cultivated with sugarcane decreases and thus the number of sugar cane farmers is decreased. Thus, I also create an *adjusted loan* ($\widetilde{Loans}_{i,t}$) variable for each type of lending or input provision activity, which is normalised by the area cultivated with sugarcane within each mill's command area at a given time t in the following way:

$$\widetilde{Loans}_{i,t} = Loans_{i,t} / area\ sugarcane_{i,t} \tag{2.1}$$

Figure 2.1 depicts the density of the normalised total value of all loans and inputs provided in the year 1930. It is clear that there is large variation of the amount of inputs and loans provided by mills. The total value per hectare farmed with sugarcane ranges from around 90¥to up to over 450¥, with a mean and median of 234.7¥and 212.3¥respectively.

Figure 2.2 shows the evolution of the four types of loans over time. Working Capital and Fertilizer make up the biggest share of total loans. What is noticeable is that both experience a strong drop previous to 1931, but while fertilizer provision rebounds strongly, working capital only reaches pre-1931 levels late in the 1930s. Overall, however, there seems to be an upward trend in the provision of credit during the 1930s, possibly as the industry was maturing.

[] The reason for the steep decline of total loans and input pro-

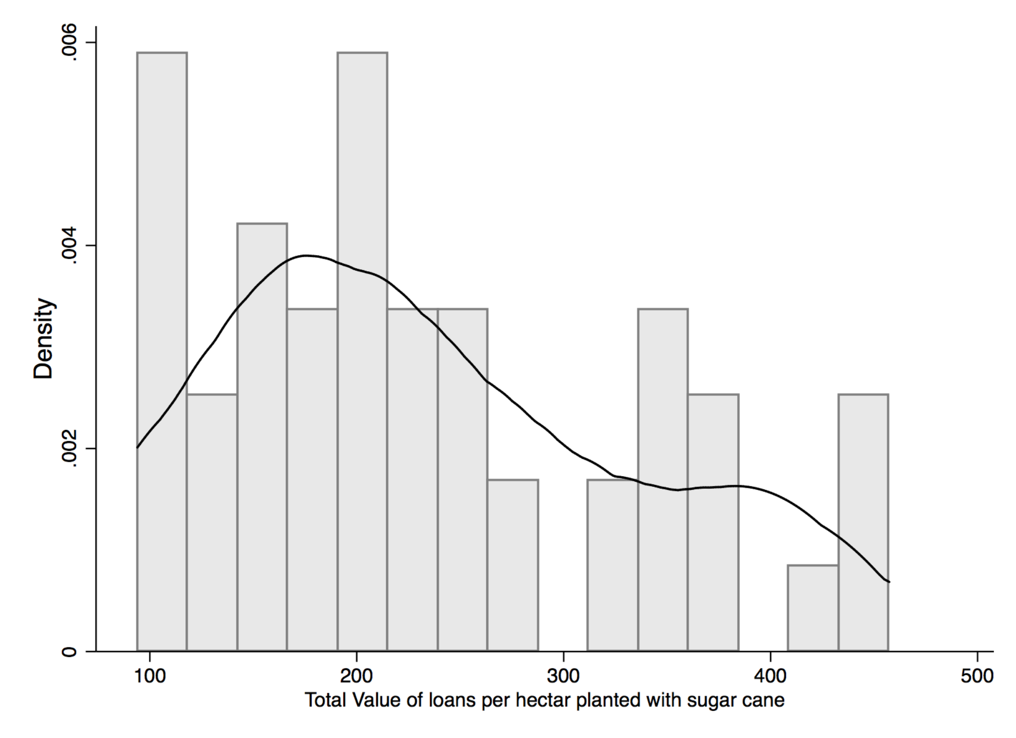



Figure 2.1: Density of Total Value of Loans and Inputs per Hectare Farmed

vided is not completely obvious. In addition to overall effects of the financial crisis, which might have decreased the liquidity of the Japanese parent companies, i t has been documented historically, that the sugar industry in Taiwan suffered severely during the early thirties, due to the fall in sugar prices in Japan (Fan, 1967). As can be seen in Figure 2.3, the total amount of loans tracks the sugar price quite closely. As sugar prices fell, investment in sugar becomes less profitable from the point of view of the mills and therefore they might have had less incentive to supply costly credit.

[]

### Mill and Farmer Data

In addition to the data on lending, I obtain a number of other outcome variables from the Taiwan Sugar Statistics on the behaviour of mills and farmers. Concerning the farmer behaviour, I digitalised data on the amount of fertiliser used, the area planted with sugarcane and yields

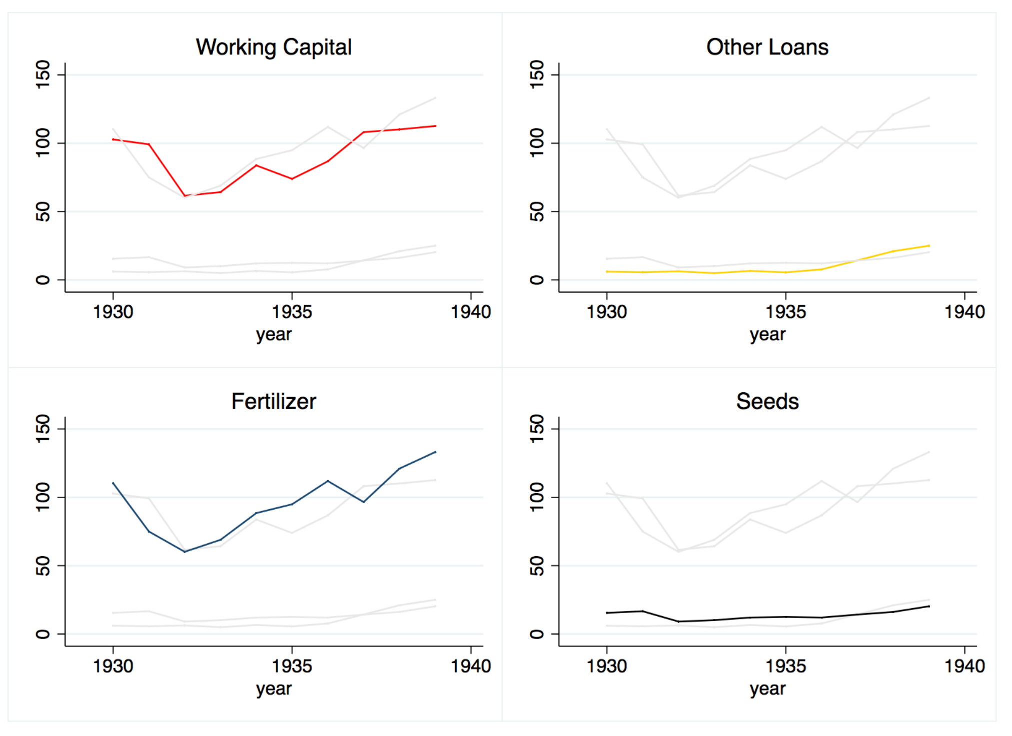



Figure 2.2: Loans by Type over Time

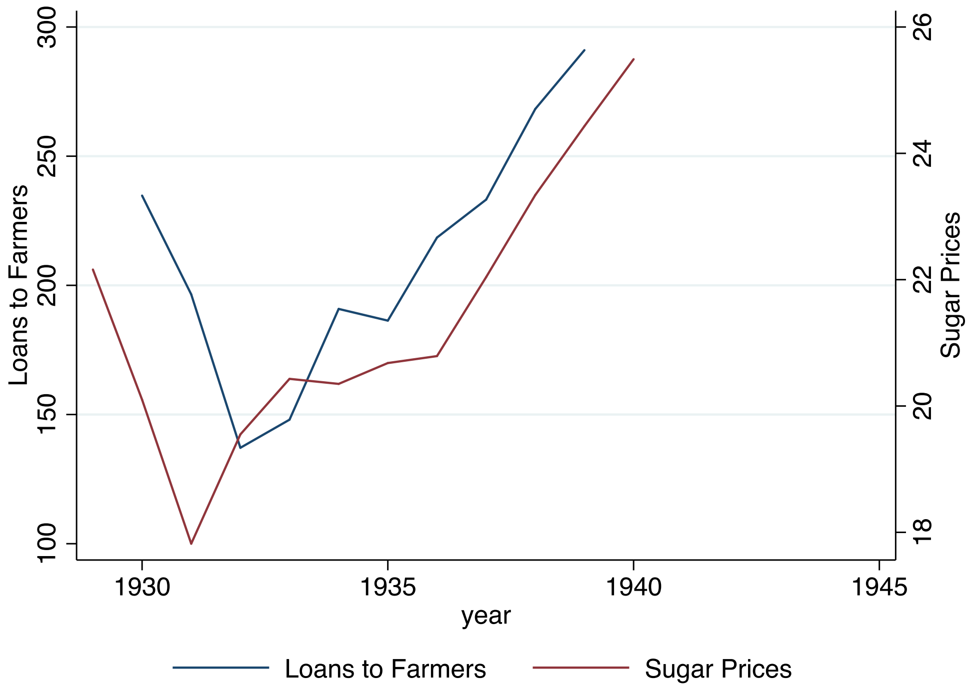



Figure 2.3: Correlation between Total Loans and Sugar Prices in Japan

by the type of field. It is important to note, that this data was reported by the mills and thus is aggregated at the mill level. Concerning the mills, I have information on the area planted with sugarcane by the mills distinguishing between paddy and dry fields and the respective yields. From this I calculate what percentage of total paddy fields or dry fields is being cultivated. Furthermore, I have information on sugar production: In addition to detailed information on sugarcane used and the amount of sugar produced, I have also a measure of technical efficiency - referred to as the sugar yield- that takes into account the quality of sugar produced. Further, I have detailed information on capital investment as well as information about the length of the harvest as well as how many days the factory was inactive during this period. The latter is of particular interest, as it is very costly for the factory to be inactive but at the same time reducing this time relies heavily on a close cooperation between farmers and mill. I further digitalised a number of variables to be used as controls, such as the equity level of the parent company in 1918, the size of the parent company in terms of number of factories, the total size of the command area as well as mill age. Unfortunately, I have no information on labour employed. It should be noted, however, that if mechanised production methods are used, labour costs are a small share of total costs in sugar milling. Table 2.1 gives the relevant summary statistics.

Finally, I also include a number of controls on the prefecture level: prefecture population, total cultivated land and per capita ownership of livestock.

### 2.3.2 Measures of Exposure to Rice Price Changes

The key variation of the empirical strategy is the degree to which mills and the farmers in their command area are affected by changes in the outside option of the farmers due to changes of rice prices in Japan. The effect of rice prices on the average farmer outside option is assumed to be a function of the average suitability of the command area for the cultivation of rice. Thus the measure of treatment intensity is the averarge rice suitability of each mill's command area.

Given Taiwan's climate, irrigation, more than soil quality, is a key

| Variable | Observation | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| | Command Areas | | | | |
| Share of Paddy Fields | 391 | .437 | .298 | 0 | .998 |
| Command Area (h) | 391 | 117349.8 | 708380.7 | 3866.285 | 4726422 |
| | Farmer Outcomes | | | | |
| Fertilizer (jin) | | | | | |
| Share of Paddy Fields - Farmers (%) | 303 | 66.8 | 5.4 | 0 | 79.5 |
| Farmer Paddy Fields Yield (Jin/h) | 470 | 126.418 | 161.228 | 11.941 | 3558.427 |
| Share of Dry Fields - Farmers (%) | 312 | 20.8 | 10.2 | 3.3 | 77.8 |
| Farmer Paddy Fields Yield (Jin/h) | 469 | 119.1 | 28.7 | 11.9 | 237.9 |
| Farmer Dry Fields Yield (Jin/h) | 496 | 97.4 | 25.7 | 31.4 | 169.8 |
| | Mill Outcomes | | | | |
| Share of Paddy Fields - Mills (%) | 342 | 9.1 | 3.53 | 0 | 44.4 |
| Share of Dry Fields - Mills (%) | 338 | 6.8 | 8.7 | 0 | 56.2 |
| Mills Paddy Fields Yield (Jin/h) | 496 | 130.5 | 37.4 | 34.7 | 258.2 |
| Mills Dry Fields Yield (Jin/h) | 496 | 113.4 | 40.3 | 18.19 | 364.1 |
| | | | | | |
| Cane Used for Production (tons) | 481 | 236.5 | 176.8 | 223.4 | 978.4 |
| Sugar Output (tons) | 482 | 30.6 | 22.5 | 0.7 | 121.4 |
| Sugar Yield (%) | 482 | 12.1 | 2.5 | 5.5 | 15.5 |
| Capital (tons) | | | | | |
| Harvest Duration (days) | 482 | 133.8 | 31.6 | 50 | 240 |
| Share of Days not Operation (share) | 479 | .415 | .378 | 0 | .98 |

No. of mills: 38

Table 2.1: Summary Statistics

determinant in whether a given field is suitable for rice cultivation, as the field needs to be flooded at the beginning of the growth cycle of rice. Fields that can be naturally or artificially flooded thus are referred to as *paddy fields*. The Japanese colonial administration distinguished thus between three types of fields: Paddy fields that are rain-fed, which means that they are only sufficiently irrigated for rice plantation once a year, paddy fields that are linked to man-made irrigation channels and thus can be cultivated twice a year and finally so-called *dry fields* that are not suitable for rice production. Sugarcane on the other hand requires less intense irrigation and thus can be grown on all three types of fields [1].

For certain years, the Taiwan Sugar Statistics contains information on the area within each command area that is of either of the three types and that is also suitable for the cultivation of sugarcane. Thus, as one of my measures of rice suitability, I calculate the share of the total land suitable for sugarcane cultivation within the command area that

[1]While sugarcane is an irrigation intensive crop, it does not however require as intensive irrigation at the one point in time as is the case with rice

are paddy fields i.e. the area within the command area that are paddy fields *and* suitable for sugarcane divided by the total land suitable for sugarcane:

$$suitability_{i,t}^{paddy} = paddy_{i,t}/total\ land_i \tag{2.2}$$

Note that while the total land within a command area is fixed over time, as the border of command areas remained unchanged, the area of fields that are paddy fields could and does indeed change over time due to improvements in the irrigation system. This causes an endogeneity issue, as mills that gain better access to irrigation might be fundamentally different from those that do not, and thus these unobservable characteristics might be driving the results. Thus, I restrict the area of paddy fields at its 1918 level, the earliest year for which the information is made available. As a result, the suitability becomes a time-invariant variable. This restricts the sample to mills that have been active since 1918 and are still active in 1930.

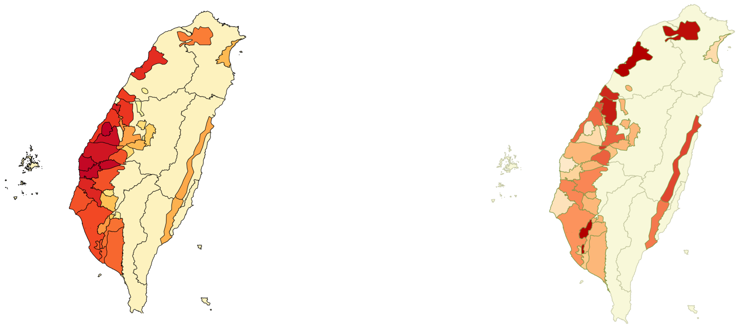
$$suitability_{i}^{paddy} = paddy_{i,1918}/total\ land_i \tag{2.3}$$

As a further robustness check, in some specifications, I restrict the measure of suitability to the share of land that are only rain-fed paddy fields and exclude all artificially irrigated fields, i.e.

$$suitability_{i}^{rain-fed} = \text{rain-fed}_{i,1918}/total\ land_i \tag{2.4}$$

In some occasions, I further use the rice suitability measure from the Food and Agricultural Organization (2016) crop-suitability data. Specifically, I use the land-suitability for wetland rice using low-level inputs, i.e. assuming no man-made irrigation is available, again to avoid endogeneity concerns. I calculate the treatment intensity variable using information about the exact GIS coordinates of the boundaries of each mills command area in 1918. While this measure is less subject to endogeneity concerns, it is also likely to be less exact as the earliest point measured is 1962. Thus, in most specification, I use the measures based on the Japanese data.

Figure 2.4b shows the suitability for rice of each of the command



(a) Cane Suitability (b) Rice Suitability

Figure 2.4: Command Areas by Crop Suitability

**Notes:** Maps are based on the FAO crop suitability index, which ranges from 1 to 9. GIS Data on the boundaries of the command areas has been compiled by the Academia Sinica's Institute. Higher suitability is indicated by darker colouring.

areas, using the FAO measure. It is clear to see that rice suitability is not randomly distributed: mills in the north have command areas that area significantly more suitable for rice cultivation than in the south. The suitability for sugar cane follows the opposite pattern as shown in Figure 2.4a. This gives rise to concerns that mills in the north are fundamentally different from those in the south and thus would have developed differently independent from the treatment. Further discussion of these concerns and what I do to address them follows in Section 2.4.3.

### 2.3.3 Prices of Rice, Sugar and Other Agricultural Goods

The price data for the agricultural products is taken from Japanese and not from Taiwanese markets, in order to avoid reverse causality concerns i.e. to rule out that price data is influenced by changes in the supply and demand of farmers and mills.

The data on rice prices comes from the historic records of the Nagoya Rice Exchange, founded in 1877 and one of the largest rice exchanges in Japan. Prices are expressed in Yen per Koku, a measure of volume equivalent to 278.3 litres. The dataset records the yearly minimum, maximum and average price for long-grain rice from 1877 until 1939. I use the minimum rice prices as a measure of prices, though results are robust to using the average price instead. Figure A.2 shows the correlation between both measures.

While changes to rice prices affect the outside option of paddy farmers, it does not take into account possible changes to the outside option of dry field farmers. Thus, similarly to before, I proxy changes to the outside option of dry farmers with the changes to the price of the main crop produced on dry fields, namely red and black beans. Bean prices are also reported in yen per Koku at the Tokyo market. The data is taken from the *Taiwan Statistical Yearbooks* (1922-1939) that were compiled by the Taiwanese Governor General's office, under the Japanese administration. They are reported annually and distinguish between red and black bean prices. I take a simple average of the two prices. In my analysis, I then focus only on changes to the relative price, which is the rice prices divided by the average bean price.

Information on the sugar prices are taken from the Taiwan Sugar Statistics, which records monthly prices for refined sugar on the Tokyo market. Prices are measured in yen per 100 jin (60kg) from 1918 until 1944. I calculate a yearly average in order to correspond to rice prices.

Figure 2.5 shows the evolution of all three prices over time. There is a clear downward trend for rice until 1931, indicated by the second dotted line. After 1931, the price begins to rise steeply. The first dotted line indicates the introduction of Ponlai rice in Taiwan, only after which the shown rice prices became salient for Taiwanese farmers. While both sugar and beans also reach their lowest point in 1931, they do not experience the same dramatic reversal as rice. Sugar prices, in particular, decrease until 1931 but remain relatively low thereafter.

## 2.4 Empirical Strategy

In this section I first determine which characteristics predict or correlate with the suitability for rice cultivation of the command area of a given mill. Then I continue by describing the empirical strategy, a difference-in-difference framework, and discussing possible concerns about identification.

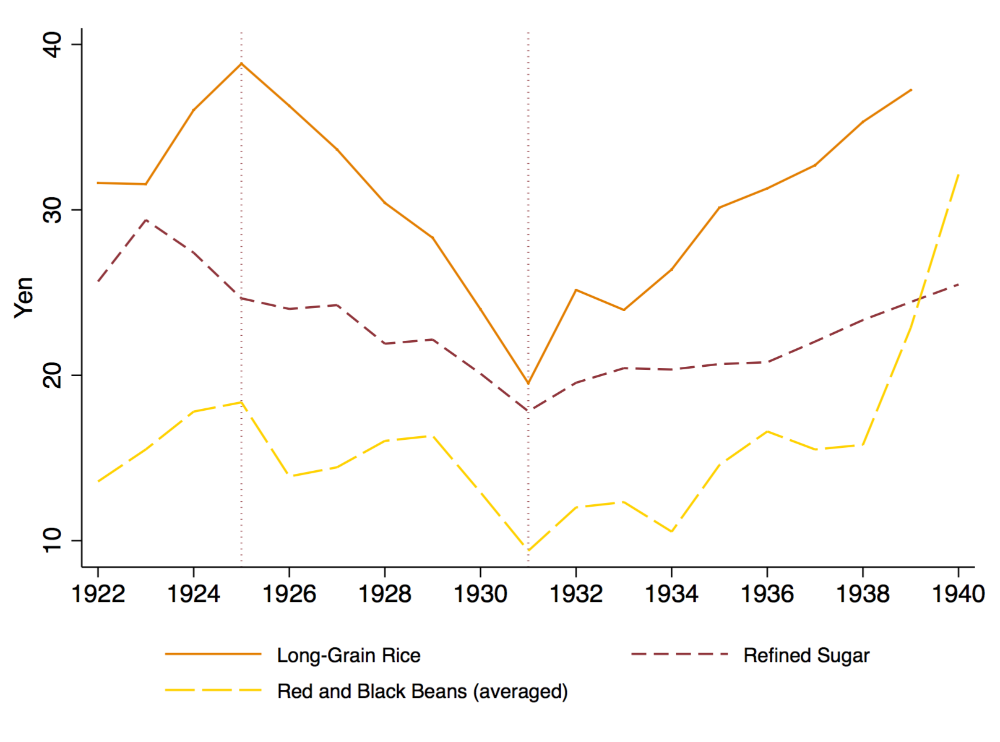



Figure 2.5: Agricultural Goods Prices on Japanese Mainland

Sugar and Bean prices are prices are measured in Tokyo while rice prices are measured in Osaka. Refined sugar price: 1 yen purchases 100 jin (60kg). Rice & Bean prices: one yen purchases one Koku (278.3 litres). Ponlai rice was available for cultivation in Taiwan only from 1925 onwards, as indicated by the first dashed line. The second dashed line indicates the timing of the change in rice policy on the Japanese mainland. 1 Japaneses Yen was equivalent of 0.5 USD at the time.

### 2.4.1 Patterns of Firm Characteristics and Rice Suitability

As can be seen in Figure 2.4b, command areas that are larger and further in the north have a larger share of paddy fields. This indicates that rice suitability is not allocated as if random, which might also imply that the common trend assumption could be violated.

In Table 2.2, I show which of the mill characteristics used as controls in the baseline regression predict the suitability for rice cultivation of its command area (i.e. the share of paddy fields). The firm characteristics included are limited to those that remain fixed after the firm is established and are in turn not affected by the share of paddy fields. I include the year the mill was established, the total size of the command area, equity of the mother company and the prefecture the mill is located in. The results are shown in table 2.2. Firstly, we can observe that a higher share of paddy fields is associated with a later year of establishment,though it disappears somewhat once prefecture fixed effects are included. This negative correlation between age and paddy share is supported by the historical literature. It is seen to be a consequence of the exclusive command area legislation, which implied that new mills could only be founded on land that was not yet within the command area of another mill. Therefore, older mills had an advantage in establishing themselves in their preferred location, which are usually in the dryer south that is more suitable for sugar cane cultivation. The results for the variables regarding the parent company are more surprising, as they indicate that larger companies are more likely to establish a mill in a location with paddy fields.

| | Share of Paddy Fields of Total Area | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Year of Establishment | .026** | .033*** | .019 | .013 |
| | (.011) | (.011) | (.014) | (.016) |
| Size of Command Area (100 000h) | | .010*** | .014*** | .014*** |
| | | (.001) | (.002) | (0.02) |
| Number of Factories owned by Company | | .015 | .013** | -.018 |
| | | (.011) | (.006) | (.027) |
| Company Equity in 1918 (million Yen ) | | | | .007 |
| | | | | .007 |
| Prefecture FE | N | N | Y | Y |
| $R^2$ | .10 | .23 | .53 | .65 |
| N | 35 | 33 | 33 | 33 |

Table 2.2: Mill Characteristics that Predict Paddy Share

Robust standard errrors are in parantheses.***p>0.001 **p>0.05 *p>0.10

I then plot the main outcome variable, total monetary loans provided, on the residual from column (4). Figure 2.6 shows that reassuringly there is little correlation.

### 2.4.2 Difference-in-Difference Estimation

The aim of this paper is to analyse the change in the outside option of a subset of farmers caused by a change in rice prices. Due to the long growing period of sugarcane, mills and farmers base their decisions in

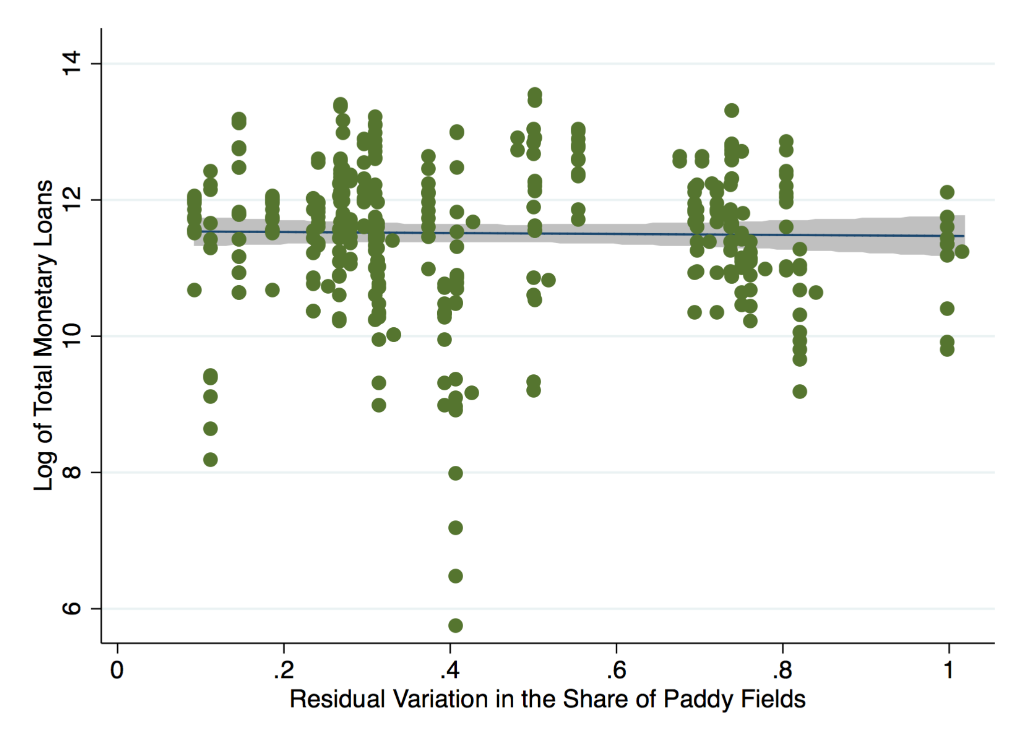



Figure 2.6: Correlation Between Residual Paddy Share and Log Total Monetary Loans

period t on the *expected* rice price in period $t+1$ and $t+2$. Thus, unexpected shocks to rice prices should only have a small impact (assuming all agents are rational). Instead, they should adapt their behaviour primarily if the change is assumed to be permanent or the *trend* in prices are changing. As outlined in section 2.2.3, in 1931 there were a number of policies that could be reasonably expected to change the level and also possibly the trend of rice prices for the future. Figure 2.5 shows that indeed the rice price experiences a dramatic change in terms of trend. Thus, in my main specification, I analyse the change of lending before and after 1931 in a difference-in-difference estimation strategy with continuous treatment intensity.

[] To highlight this point, one could consider the incentive constraint in a simple credit model of strategic default with a single model as is proposed in (Ghosh et al., 2000). Suppose that there is a single lender, which in this case is the mill. There are three periods: In period t-1, the mill announces a contract consisting of $L_t$, which is the loan it is willing to supply, $r$, the interest rate of said loan and $y_t^c$, which is it's payment for the sugarcane sold by the farmers. Farmers observe this contract and in period t decide whether to plant sugarcane or rice. For simplicity assume that this is a binary decision. The planting decision is an essence already a decision on whether the farmer wants to default on the loan: If the farmer plants sugarcane, he or she is forced to repay the loan, as the mill is a monopolist and will simply deduct the loan repayment, i.e. if the farmer decides to plant sugarcane, in period t+1 he or she harvests the cane and sells it to the monopolist, for $y_t^c - (1+r)L_t$. If the farmer, however, has taken out a loan and decides to plant rice, the mill imposes a large fine. Therefore, repayment is likely to be impossible or not desirable. Therefore, if the farmer has planted rice, in period t+1, he or she will default on the loan. In this case, the farmer earns income $y_t^r$ form his or her rice harvest. Suppose that $y_t^r < y_t^c$ The time line can also be seen below:

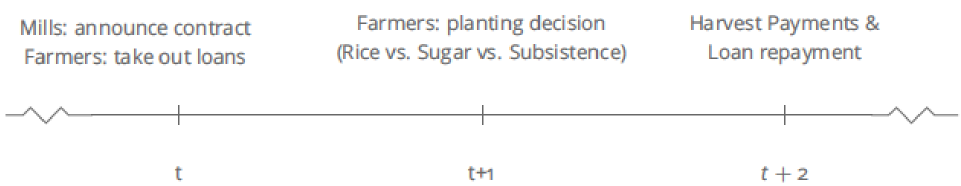



Figure 2.7: Timeline

In the case of default, the mill historically imposed heavy fines, which I assume in this case implies that the farmer is no longer able to either borrow from nor sell to the mill and therefore is no longer able to produce sugarcane. Supposing that the farmer has a discount factor of $\delta$, it can be shown easily that the farmer only repays his or her loan if the following incentive constraint is satisfied:

$$IC: \sum_{t=0}^{\infty} \delta^t \Big(E_t\left[y_t^c\right] - (1+r)L\Big) \geq \sum_{t=0}^{\infty} \delta^t \Big(E_t\left[y_t^r\right]\Big) + L \tag{2.5}$$

The equation above implies that the farmer only repays the loan if the future expected pay-off of planting cane minus the repayment value is larger than the future expected pay-off from planting rice. It can easily be seen from the above equation that this incentive constraint is more likely to bind if expectations about future rice prices are higher keeping cane prices fixed. In this way contemporaneous prices should only matter for informing expectations about future prices. This is in part, because decisions about defaulting are made at the planting stage and therefore by design future prices are the relevant statistic and in part due to the fact that by defaulting the farmer closes off the possibility of selling sugarcane to the mill in the future. The latter means that while the first period's prices are important, expectations about the *price trend* are even more important for the decision. As a result, the empirical strategy will primarily focus on the change in trends, though I also use contemporaneous prices in some specifications []

As variables are reported at the mill level, the treatment intensity varies also at the mill level and depends on the share of fields within a command area of the mill that are suitable for rice production. In my baseline specifications this is measured as the area of paddy fields as a share of the total area within the command area that are suitable for sugarcane cultivation, as outlined in equation 2.3.

The panel data structure of the data allows me to include both year and mill-level fixed effects, which implies that all unobserved time invariant mill and farmer characteristics, as well as any year effects that are common across all mills are absorbed. However, imbalances between factories with a high and low paddy share could be associated with differential time trends. As most paddy fields are in the north of Taiwan, the two samples are indeed not balanced. Thus, I further include prefecture specific time trends. In addition, I include time-varying prefecture controls to capture non-linear trends, such the population working in agriculture, the total cultivated land in the prefecture and the number of cattle per capita as a proxy for rural incomes.

I do not use factory level time-varying controls except age, since these are potentially endogenous to treatment and could lead to bias (see for example Angrist et al. (2009)). I do include two time-invariant mill characteristics that I interact with the post-dummy, namely parent-company capital in 1918 as well as total size of the command area. The final specification therefore becomes:

$$y_{i,t} = \alpha_0 + \alpha_1 post_t \cdot paddy_i + \theta_i + \gamma_t + prefecture_p \cdot t + age_{i,t} + \mathbf{X}_i \cdot post_i + \varepsilon_{i,t} \tag{2.6}$$

where $y_{i,t}$ are the factory-level outcomes at time t, $\theta_i$ and $\gamma_t$ are the factory and time fixed effects respectively, and $prefecture_c \cdot t$ are the region specific time trends. $age_{i,t}$ denotes the age of mill i at time t, and $\mathbf{X}_i$ are time-invariant mill controls The main variable of interest is the interaction of $post_t$, a dummy that equals 0 at time $t \leq 1931$ and equal to 1 otherwise and $paddy_i$, the share of paddy fields of total area suitable for sugarcane cultivation within the command area of a given mill measured in 1918. The effect thus represents the average change in lending across all time periods after 1931 proportional to the share of paddy fields.

The main regression analyses the effect on the value of loans dispensed and inputs provided. However, a decrease in total value might simply be caused by a reduction in the amount of sugarcane being cultivated. Thus the main variable of interest is the value of loans (and inputs provided) in Yen normalised by the area in hectares that is used for sugarcane cultivation in the same year. While this does not exclude that the effects observed are caused by a reduction in demand, it does rule out the purely mechanical channel of reduced production that could be driving a possible reduction in lending.

**Trend break vs. Price Changes**

The empirical strategy outlined in the previous section, concentrates on the the break in trends of rice prices, and not primarily on the actual price in each period. This is due to the fact t

### 2.4.3 Identification concerns

The coefficient in the above regression captures a causal effect only if the so-called parallel trend assumption is satisfied, i.e. that mills with different shares of paddy fields would have experienced the same trend over time in absence of any treatment. This would ensure that the observed effect is not caused by differential trends that are not due to the change in rice prices.

One way of addressing this concern is to check whether mills with different treatment degrees exhibit parallel trends before the treatment takes place. This is somewhat challenging for the main variables of interest, lending and the provision of inputs, as these are recorded the earliest in 1929. Therefore, there are just two time periods before 1931, the year price trends changed. Figure 2.8 shows the average total value of all loans as well as of the inputs provided over time split up for mills with a higher or lower than median share of paddy fields. Note that given that rice prices are not constant before 1931, we do not necessarily expect the pre-trends of the two groups to be perfectly parallel. It would be important however, that the pre-trends are not such that they contribute in explaining the treatment effect we observe. Figure 2.8 shows that, in the two periods before treatment, 1929 and 1930, the two groups experiencing a near identical trend. Figure A.3 shows the same trends for loans and for the two inputs, seeds and fertiliser, separately. Again, pre-1931, the trends seem very similar. Though this is reassuring, it is important to note the two periods may not be sufficient in order to establish a parallel trend.

Next, as a second test, I interact the share of paddy fields with 9 yearly dummies, leaving out 1931 as a reference year, which allows for a more explicit test of the parallel trends. If we mills with a higher share of paddy fields experienced lower lending before the change in price trends, this should appear in the coefficients. Finally, I conduct the same tests as above on other mill and farmer outcomes, which I observe over a much longer time period and in earlier years. More specifically, I make use of the fact that the exportable, long-grain Ponlai rice was only introduced in Taiwan in 1925. Thus, previous to that date, rice prices in Japan should have no (or lesser) effect on mills and farmers in Taiwan, and thus we would expect to observe a parallel trend before 1925. Results of both tests are presented as robustness checks in section 2.5.2.

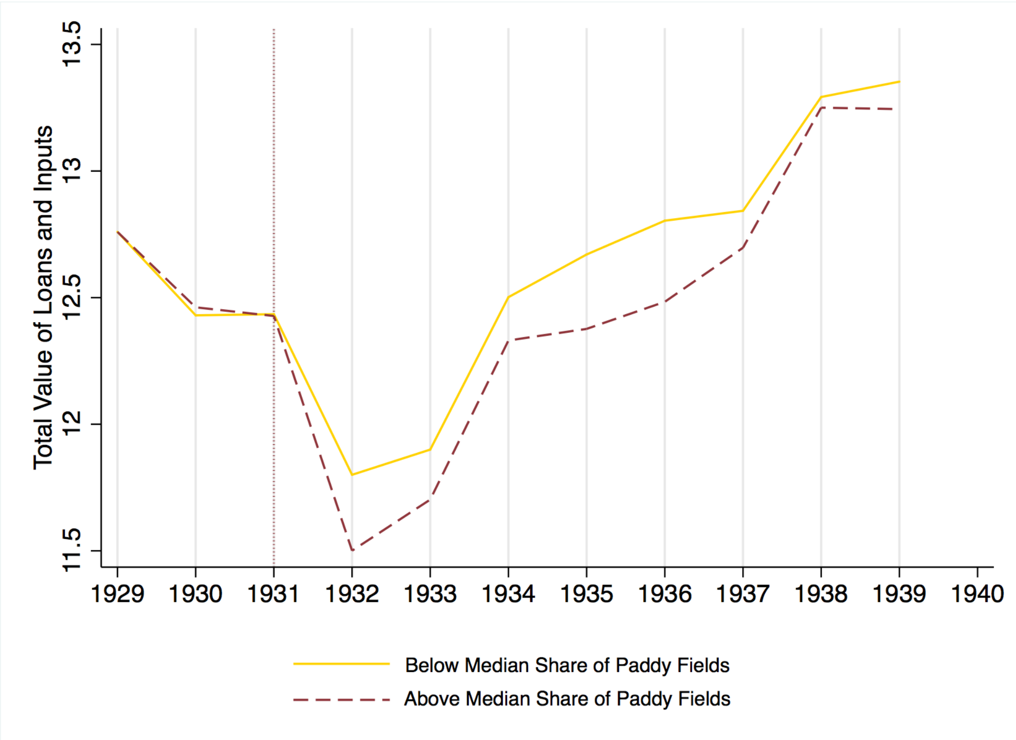



Figure 2.8: Average of Log of Total Value of Loans and Inputs Provided

The total value of loans and inputs for mills with less than median share of paddy fields is normalised to equal those of mills with above median share in the year 1929. Values are expressed in loged Yen.

## 2.5 Results on Lending

### 2.5.1 Baseline Results

Table 2.3 shows the results of the regression as described by equation 2.6. The main outcome variable is the total value of loans and inputs provided by the mill to the farmers divided by the number of hectares farmed with sugarcane, which is shown in columns (1) to (3). Column (1) shows the basic difference-in-difference estimation without any controls or fixed effects. Interestingly, while a higher share of paddy fields is associated with a higher value of loans and inputs provided, the interactive term is negative and significant at the 95% level. A one standard deviation increase in the share of paddy fields decreases the value of loans and inputs provided by close to 19¥. Inclusion of prefecture and year fixed effects as well as prefecture time trends in column (2) only strengthens the result and total lending is now reduced by 24.4¥. This represent around 11% of the average value of loans and inputs provided. Column (3) includes further time-varying prefecture controls as well as time-invariant mill controls interacted with a post-1931 dummy. The coefficients remain nearly unchanged; however, the sample size is somewhat reduced due to missing values for some of the mill control variables. Column (4) to (7) show that the decrease is clearly driven by a decrease in monetary loans. Column (4) and (5) show that a one standard deviation increase of paddy fields causes loans to fall by 25.6 ¥ per hectare, which increases to 26.8 ¥ per hectare when mill and prefecture controls are included. Given that average value of loans provided is around 103¥/hectare, this constitutes a fall of over 26%. Inputs provided by the mills of the farmers, however, remain unchanged as can be seen in columns (6) and (7). Table A.4 conducts the same exercises using the logged value of the same outcomes as in Table 2.3. While the magnitude of the coefficients represent a slightly larger percentage change, they are less precisely estimated and lose significance, when the full set of controls are used. Table A.6 goes further in splitting loans according to type, which support the findings in Table 2.3.

The results of the baseline specification are consistent with a decrease in the sustainability of relational contracts between mills and farmers. The fact that the effect is driven exclusively by the decrease in fungible loans and that non-fungible inputs are nearly unchanged supports the hypothesis that this effect is driven by the increase by farmers' incentive to default. If the effect was purely caused by a decrease in field quality used for can cultivation or a decrease in demand for cane related inputs, there should be a similar negative effect on the provision of inputs. However, compositional effects may well play an important role as more credit worthy farmers might have switched to rice production.

One concern with my findings is that the results might be driven by serial auto-correlation within the dependant variable. While, this is a stronger concern when the number of states is small relative to the number of time periods, I investigate this concern following the method proposed by Bertrand et al. (2004), by collapsing the data into a single pre- and post-period. While likely reducing power, this should remove the auto-correlation without relying on parametric estimates that do not usually perform well with such small sample size. The results are shown in Table A.5. While the effect on total loans per hectare cultivated with cane looses its significance, the results for monetary loans remain robust.

| | Total Lending & Inputs ¥/hectare | | | Monetary Loans ¥/hectare | | Inputs Provided ¥/hectare | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| post* paddy | -18.923** | -24.420** | -24.662** | -25.593*** | -26.828*** | 1.201 | 2.739 |
| | ( 8.094) | (11.983 ) | (10.799) | (9.200) | (7.691) | (4.696) | (5.191) |
| post | 19.153 | | | | | | |
| | (12.879) | | | | | | |
| paddy | 153.097*** | | | | | | |
| | (48.561) | | | | | | |
| Factory FE | N | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | N | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | N | Y | N | Y | N | Y |
| Mill Controls | N | N | Y | N | Y | N | Y |
| N Mills | 38 | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 360 | 291 | 360 | 291 | 360 | 291 |
| $R^2$ | .014 | .853 | .860 | .837 | .824 | .802 | .816 |
| Mean | 209.74 | 209.74 | 209.74 | 102.93 | 102.93 | 106.89 | 106.89 |

Table 2.3: Loans and Inputs Provided Per Hectare Cultivated with Cane

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

Finally, I replace the treatment variable with the interaction between the average price of long-grain rice in Japan and the share of paddy fields, in order to see the direct effect of rice prices. It is important to note that I use here the lagged prices, as these are the relevant prices at the time when loans are issued and inputs given out. The results are shown in Table A.7. Interestingly, as can be seen in Columns (6) and (7), when using rice prices, we can find a positive effects on input provision. This could be explained by mills substituting away from more fungible loans are are due to the improved bargaining position of farmers, as rice prices increase in the short run. Table 2.4 then investigates this further and includes both variables in the regression. Column (2), (4) and (6) show the results with both variables. It seems that prices have no direct effect on lending, but instead the change in trends, as captured by the post-1931 dummy, has a significant negative effect. The opposite is true for the inputs provided. Here, the short run price shocks seem to have a positive effect on the value provided per hectare. This again could be caused by the improved bargaining position of farmers or mills trying to compensate for the decrease of fields cultivated with sugarcane.

| | Total Lending & Inputs ¥/hectare | | Monetary Loans ¥/hectare | | Inputs Provided ¥/hectare | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $price_{t-1} * paddy$ | -3.380 | 11.328 | -12.351** | 2.131 | 9.306*** | 10.611** |
| | ( 7.678) | (10.162 ) | (5.718) | ( 6.811) | (3.520) | (4.282) |
| $post * paddy$ | | -29.737** | | -27.891** | | -2.516 |
| | | (12.408) | | (9.336) | | (5.817) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | Y | Y | Y | Y | Y | Y |
| Mill Controls | Y | Y | Y | Y | Y | y |
| N Mills | 38 | 33 | 33 | 33 | 33 | 33 |
| N Observations | 291 | 291 | 291 | 291 | 291 | 291 |
| $R^2$ | .854 | .861 | .811 | .823 | .819 | .820 |
| Mean | 209.74 | 209.74 | 102.93 | 102.93 | 106.89 | 106.89 |

Table 2.4: Baseline Specification Including both Prices and Post-1931 Dummy

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

### 2.5.2 Robustness

In this section, I investigate the robustness of the baseline results. The key assumption that needs to hold in order for my results to be valid is that mills with different levels of rice suitability would have experienced parallel trends in absence of treatment. As outlined in Section 2.4.3, I try to test for this assumption in two ways: firstly, I include prefecture-year fixed effects as well as mill-specific linear trends. Secondly, I allow for non-linear effects.

Table A.8 shows the results on fungible lending when prefecture-year fixed effects and linear mill trends are included. Prefecture-year fixed effects capture all the variation that is caused by non-linear prefecture specific trends. Including linear mill time-trends means that our coefficients no longer capture any linear changes at the mill level over time. Columns (2) and (3) display the effects for the prefecture-year fixed effects, first without and then with mill controls. The negative effect on lending remains robust and the magnitude of the coefficients also remains similar. Columns (4) shows the coefficients for the baseline equation is augmented for linear mill time-trends, and Column (5) shows the same when prefecture controls are included. Again, the results remain robust.

The results for the non-linear effects specification are shown in Table A.9 as well as in Figures 2.9 and A.4. As mentioned above, unfortunately, lending data is only recorded for two time periods prior to treatment and thus there is a limit how informative this is about the pre-trends. Due to missing values for the area farmed in 1929, here the log total values are shown. Reassuringly, Figure 2.9 and Table A.9 show that the negative effect of treatment on lending only sets in after 1931.

Another concern I address is the endogeneity of my measure of rice suitability, i.e. the area suitable for rice cultivation as a share of the total area that is suitable for growing sugarcane. As the majority of paddy fields are created through the construction of irrigation channels, more productive mills or farmers might invest in better irrigation. Even though in most cases, this endogeneity should work in the opposite direction than indicated by the coefficients, as a robustness check I limit my measure to the area of fields that are rain-fed paddy fields and thus arguably a more exogenous measure. The results are shown in Table 2.5. The basic pattern remains the same as in the baseline specification: Total loans decrease, which is driven by a fall in loans while the provision of inputs remains unchanged. The effect seems around half as big as the The share of rain-fed paddy fields capture actual rice suitability much more imperfectly and thus it is to be expected that the coefficients are smaller and somewhat less precisely estimated.


Figure 2.9: Time-varying Treatment Effect Estimates on Log Loans (monetary)

**Notes:** The outcome variable is the log value of all monetary loans. Confidence intervals shown are at the 99%, 95%, 90% and 80% levels. The reference year is 1931.

## 2.6 Other Outcomes

In this section, I present the effects of the change in rice price trends on other behaviours of farmers and mills.

### 2.6.1 Farmer Outcomes

The outcome variables concerning farmer behaviour are firstly the area cultivated with sugarcane, the use of fertiliser and subsequent yields of fields farmed.

The changes to the area of fields cultivated with sugarcane, distinguishing between paddy and dry fields, are shown in Table A.10. The results are as would be expected independent of any breakdown of relational contracts: Column (1) and (2) display the effects on the total area cultivated with sugarcane, where we see a small but non-significant de-

| | Total Lending & Inputs ¥/hectare | | Monetary Loans ¥/hectare | | Inputs Provided ¥/hectare | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -11.651 | -13.955** | -10.950** | -14.396*** | -.564 | .613 |
| | (7.243) | (7.040) | (5.468) | (4.450) | (3.961) | (4.632) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | Y | N | Y | N | Y |
| Mill Controls | N | Y | N | Y | N | Y |
| N Mills | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 291 | 360 | 291 | 360 | 291 |
| $R^2$ | .841 | .829 | .830 | .815 | .772 | .816 |
| Mean | 209.74 | 209.74 | 102.93 | 102.93 | 106.89 | 106.89 |

Table 2.5: Baseline Results Using Rain-Fed Paddy Fields Only

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

crease in the total area. When splitting the regression by type of field, we see that there is a large and highly significant decrease of paddy fields that are used for sugar cultivation of between 47-51% (see Column (3) and (4)). Column (5) and (6) show that this decrease is offset by an increase in dry fields on which sugarcane is grown of between 12.5% and 21.5%. While these effects are not very surprising, they do however give support to the hypotheses that the post-1931 captures only an effect related to rice prices, as it affects the two types of fields such an asymmetric way.It is also important to note that the results do not simply indicate the straight forward propositions that a permanent increase in rice prices decreases the area cultivated with sugarcane, but instead that this increase decreases sugarcane cultivation *more than proportionally* in areas with a larger share of paddy fields.

Another outcome of interest is the usage of fertiliser by farmers.Firstly, I use the data on actual fertiliser usage to see if my presumption that the fertiliser provided is non-fungible and thus it should be employed for cane cultivation. Figure A.5 shows the correlation between fertiliser provided and fertiliser consumption. The correlation is around 1.111 and very strong. Indeed there are only few observations clearly below the 45 degree line. Note that we would expect that the actual fertiliser consumption should be larger than what was provided from the mills, as fertiliser consumption also includes traditional fertilisers, such as animal manure. The effect on fertiliser consumption are displayed in Table 2.6. Column (1) and (2) show the effect on the logged value in Yen, which is virtually unchanged by treatment. Further, column (3) and (4) show the effect on the fertiliser used per hectare cultivated with sugarcane in the same year. Again there is no significant effect. Finally, in column (5) and (6), I investigate whether the treatment has an effect on fertiliser consumption relative to the value provided by the mills. A negative coefficient could for example imply that farmers divert provided fertilisers to other crops, or would decrease their spending on additional fertiliser. However, again the coefficients are insignificant.

The final farmer outcome are sugarcane yields shown in Table A.11. Column (1) and (2) show the effect on all field types, while the subsequent columns distinguish between paddy and dry fields. The treatment effect is negative overall, which however could have been explained by the change in the share of paddy fields of the area being cultivated with sugarcane, given that the yield of paddy fields is significantly higher than for dry fields. When running separate regressions for each type of field, it can be seen that the negative effect exists *within* both field categories. This could be due to decreased yield per field or instead due to compositional changes of fields, due to both the increased outside option but also possibly due to the lower provision of credit by the mills. Unfortunately, I do not have field level information and thus cannot distinguish these two channels.

### 2.6.2 Mill Outcomes

Finally, I analyse how the production of sugar by mills with a higher share of paddy fields is affected after the permanent change in the trend of rice prices. The information available on various stages of produc-

| | Log Total Value | | Fertiliser ¥/hectare | | Actual Usage/Provision | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -.007 | -.005 | 3.189 | 2.382 | -.094 | -.067 |
| | (.068) | (.073) | (6.529) | (5.206) | (.090) | (.049) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | Y | N | Y | N | Y |
| Mill Controls | N | Y | N | Y | N | Y |
| N Mills | 42 | 33 | 42 | 33 | 42 | 33 |
| N Observations | 360 | 360 | 291 | 360 | 291 | 291 |
| $R^2$ | .841 | .829 | .830 | .815 | .772 | .816 |
| Mean (piculs) | 251827.3 | | 114.468 | | 1.643 | |

Table 2.6: Effect on Fertiliser Consumption

**Notes:** In the last two columns the dependent variable is divided by the value of inputs provided by the mill. The independent variable has been normalised such that one unit equals one standard deviation. prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

tion is quite detailed, however, I use information on the total amount of cane used in production, the amount of sugar produced, the mechanical efficiency of converting cane into sucrose, called the sugar yield, and daily crushing capacity. Further, I have information about the harvest duration as well as on the percentage of days during the harvest season that the mill is inactive. The results are shown in Table A.12. None of the production variables seem affected except for the share of days during harvest time that the mill remains inactive, shown in Column (5). Mills with a one standard deviation higher share of paddy fields are inactive for 2.2% more of the harvest duration. Ensuring a coordinated and consistent harvest schedule is one of the key managerial aspects in increasing productivity and requires close coordination with the farmers. A deterioration of the coordination of the harvest may be caused by the relationship with mills becoming less important for farmers, as rice becomes a more profitable crop.

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## 2.7 Alternative Explanations

While the above results are consistent with a reduction in the supply of credit caused by an increased fear of default, they could also be explained by alternative hypotheses. There are two alternative explanations: Firstly, the observed effect could be caused by a decrease in the demand of credit and secondly, the supply of credit by mills could be reduced due to reasons unrelated to the fear of default. I find suggestive evidence, however, that these alternative hypotheses are not supported by the data.

### 2.7.1 Decreases in Demand for Credit

Understanding whether the decrease in credit is caused by demand or supply effects is crucial for understanding the effect on farmer welfare and market efficiency: If the demand for credit is simply reduced, markets should function equally efficiently and the policy would have increased farmer welfare. On the other hand, if the observed effects are caused by credit rationing, then this would imply a decrease in efficiency and ambiguous effects on farmer welfare. Even though I normalise the amount of loans by the area planted with sugarcane in a given year, increase in the price of rice caused by the policy might lead to a decrease in the demand for credit for a number of reasons. First of all, farmers might have a reduced need for credit due to increased incomes from rice. This is, however, contradicted by the negative effect on revenues earned per hectare farmed with rice. Furthermore, areas with more paddy fields might have been cultivated longer and thus have better access to informal networks or even formal lending. This is not supported by the data, as in a cross section a larger share of paddy fields is actually not correlated with a higher amount of loans being provided in 1929, as was shown in Figure 2.6.

The most serious concern is that the demand of credit is reduced due to compositional effects. This would be the case if more credit constraint farmers happen to have a higher relative suitability for rice cultivation, for example as small farms produce higher yields in rice compared to sugarcane. However, I can use the timing of the effect to rule out this explanation. While the policy was announced in 1931 and the treatment effect on loans is large and significant immediately, as was shown in Figure 2.9, the actual rice price took several years to rise above the 1929 level. Interestingly, as can be seen in Figure 2.10, the share of paddy fields planted with cane only decreased in later years and follows the actual rice price quite closely. Therefore, the decrease in loans *preceeds* the fall in the area planted with cane, making compositional effects less likely though not impossible, due to the aggregate nature of the data.

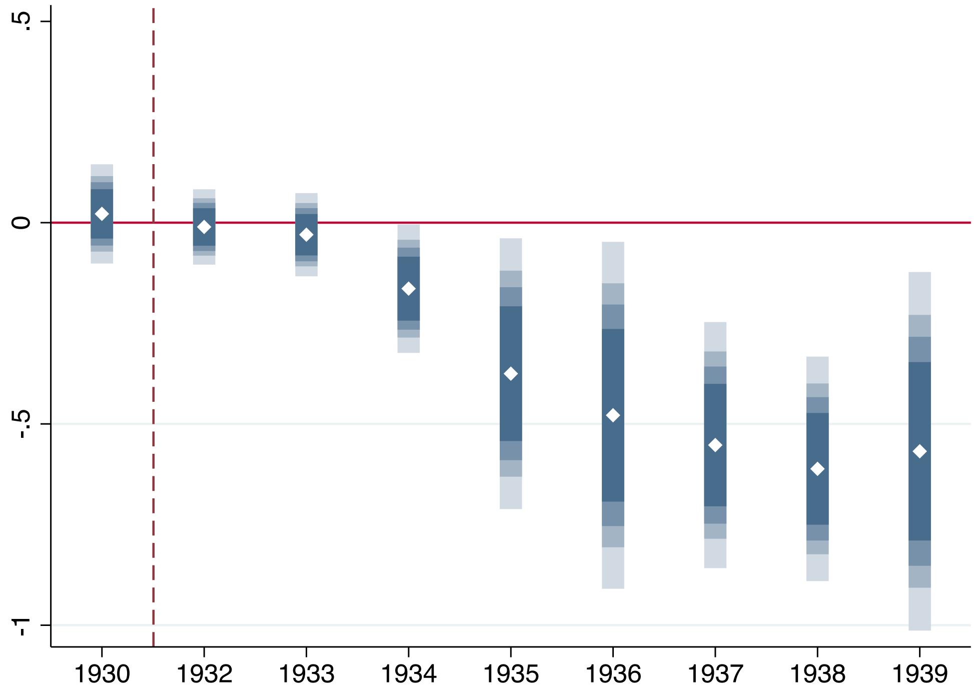


Figure 2.10: Time-varying Treatment Effect on Share of Paddy Fields Planted with Cane

**Notes:** The outcome variable is the log value of all monetary loans. Confidence intervals shown are at the 99%, 95%, 90% and 80% levels. The reference year is 1931.

### 2.7.2 Other Decreases in Supply of Credit

Even if the results are not caused by a reduction in demand, the contraction of the supply of credit might be unrelated to the perceived risk of default. For example, mills might have found alternative more lucrative investment opportunities, for example in rice production. In this case, however, we would expect there to be a reduction in other mill variables that are affected by decreased investment but unaffected by default rates, such as sugarcane farming undertaken by mills themselves or the provision of inputs. Results on the cultivation of sugarcane by mills is shown in Table A.13, which shows the area cultivated and yields for both types of fields. In contrast to farmer cultivation, the change in rice prices does not seem to have any significant effect. Similarly, the provision of inputs, both seeds and fertilizer, are unaffected by the treatment as can be seen in Table A.14.

A further concern might be that mills themselves become more credit constraint due to a reduction in their expected profits. As a result they are more liquidity constrained and less able to provide loans. If this were the case, we would expect this effect to be larger for mills that belong to smaller parent companies. I measure size of the parent company as a) the equity of the company in 1918 and b) as the number of mills belonging to the parent company. Table A.15 shows, however, that there is no heterogeneous effects according to size. Finally, I investigate whether the negative effect is higher or lower for mills whose command area includes a district court in 1928, which I use as a measure of enforceability. Table A.16 shows that the negative effect of the policy is mitigated by around a third for mills who have a court located in their command area. This mitigation, however, only occurs for loans and not for inputs provided, reducing concerns that the presence of a court proxies for lower credit demand or unobservable mill characteristics.

### 2.7.3 Other Types of Contracts

Even if the effect is driven neither by changes in the demand for credit nor in outside changes in the supply, unrelated to repayment rates, it is not yet clear that relational contracts need to be crucial here. Instead there could be alternative contracts that underlie the observed changes.

I discuss two possible alternative sets of contracts.

**Strategic Default within a Spot Contract**

One of the most obvious alternatives to a relational contract is the possibility that credit rationing occurs due to strategic defaults in a single period contract. Lending under relational contracts can be self-enforcing due to the threat of losing the long-run trading relationship in the case of default. However, the increase in rice prices could lead to an increase in defaults even in the absence of a longer term trading relationship, as the incentive to default and grow rice instead of sugar is increased in each period. In this case, we would have a similar incentive compatibility constraint as in equation 2.5. However instead of the farmer comparing the total expected future value of the relationship, he or she simply compares the pay-offs in each period, i.e. it would simply become:

$$IC : \delta^t \Big( E_t \left[ y_t^c \right] - (1+r)L \Big) \geq \Big( E_t \left[ y_t^r \right] \Big) + L \tag{2.7}$$

This could be the case for example because farmers are myopic or because the threat of severing the trading relationship is either not enforced or not believed.

While the baseline results are consistent with this set of contracts, we would expect in this case the most important factor to be the contemporaneous rice price and not the break in the rice price trend. This, however, is inconsistent with the results in Table 2.4, which shows that if we include both actual prices and the trend-break dummy in the regression it is the latter that explains the changes in loans. However, if switching costs are large, one could imagine that the planting decision becomes a forward-looking decision and should depend on the expectation of future prices instead. In this case, we can no longer distinguish between a spot lending contract and a relational contract.

**Asymmetric Information**

A more serious concern is that the increase in rice prices causes a change in the composition in borrowers, which leads to credit rationing by aggravating asymmetric information issues. Asymmetric information about the 'quality' of the borrower could lead to credit rationing as mills cannot charge high enough interest rates to make lending profitable given the riskiness of cane production. Similarly as discussed in a previous section, it could be that land that is more suitable for rice cultivation is also a more suitable or less risky land for sugarcane cultivation, and therefore as farmers switch to rice production the composition of the pool of lenders is changed. Therefore, in the presence of switching costs, such a mechanism could also produce a negative relationship between the expected rice price and lending.

However, in this case we should most likely see that a change in lending to go hand in hand with a switching of farmers to paddy fields. However, as mentioned in section 2.7.1, we see a strong decrease in loans to sugarcane farmers before we see a change in the area of paddy fields or dry fields farmed with rice and sugarcane. Of course the data is aggregated and not on a field by field basis and I cannot rule out that the composition of fields has changed. I further test whether land that is particularly suitable for rice cultivation is particularly suitable for sugarcane at an aggregate level by regressing the FAO suitability index for rice on that for sugarcane. I find a strong negative correlation, as can be seen in Figure A.6.

## 2.8 Conclusion

This paper analyses the effect of a change in the outside option of a subset of farmers on mill-to-farmer lending and provision of inputs. More specifically, I investigate how a permanent change in the price of rice, the main alternative crop for a subset of farmers, affects lending in the case of the sugar industry in colonial Taiwan. Under perfect contract enforcement, improving farmer outside option should improve their bargaining position and thus increase lending, if such demand exists. However, under the weak contract enforcement during the colonial period, such lending was likely to be supported by relational contracts. In this case, improvements to outside options reduce the relative importance farmers place on the relationship with the mill, which might reduce informal lending and thus contribute to reducing farmer welfare. The evidence presented in this paper shows that the latter seems to be the case. I observe that more affected mills provide significantly less monetary loans to their farmers, even though the provision of inputs remain the same. The area farmed with sugarcane remains stable and fertiliser usage remains unchanged, but yields are severely decreased, pointing at either incentive or compositional effects. Further, mills that are more exposed to the change in rice prices seem to be less able to organise harvesting efficiently. While the current evidence presented indicates a deterioration of relational contracts, there is little yet to be said about farmer welfare. Thus in current work in progress, I am digitalising data on the sub-prefecture level, which gives me information about the majority of crops produced and thus allows me to more accurately make statements about the welfare implications.

# Chapter 3

# The Benefits of the Bamboo Network in International Trade

## 3.1 Introduction

Non-tariff trade costs have been the focus of the empirical trade literature since the seminal contribution of Obstfeld and Rogoff (2001). These trade costs appear to be large and important determinants of trade flows across countries. However, they are still not well understood. The key empirical challenge is that non-tariff barriers are inherently unobservable. The study of the role of ethnic networks in facilitating trade allows us not only to document the importance of unobservable frictions, but also to shed light on their nature; in fact, ethnic networks are helpful for overcoming only some of these barriers. Although the importance of ethnic networks in promoting trade has been widely documented (Rauch and Trindade, 2002; Rauch, 2001, 1999; Parsons et al., 2014), there is still little consensus on the exact channels at play, which is often due to the aggregate nature of the available data.

In this paper, we add to the literature by studying the effect of ethnic networks using firm level data from Guangdong Province, China. The network in question was created after a mass migration wave of ethnic Cantonese people from Guangdong to the United States in the late 19th century. We study the effect of improved access to the the ethnic network in the U.S., which we define as the network of American-born ethnic Cantonese residing in the United States.

Our identification strategy makes use of the diversity of ethnicities and languages in Southern China. We calculate the degree of exposure to ethnic networks of firms in Guangdong as the interaction of two dimensions. Firstly, an industry dimension: we assume that a given firm's exposure to the network increases with the number of ethnic Cantonese workers employed in industries that it is likely to have trading relationships with. We propose that a Chinese firm is more likely to trade with U.S. firms operating in the same 4-digit industry, with downstream manufacturing buyers, or with retailers and wholesalers, which sell the goods it produces. Therefore, we calculate three different measures of network exposure at the industry level, corresponding to the number of ethnic Cantonese workers in each of those related industries.

Secondly, according to our measure, firms' network exposure increases with cultural closeness to the ethnic network in the U.S. For this measure we exploit the geographic location of firms: "cultural exposure" to the network is higher for firms located in one of the sending counties of migrants in the 19th century. This flows through two channels. Firstly, there may still exist kinship ties, i.e. the descendants of the migrants in the U.S. may have maintained relations with individuals in the place of origin. The second channel is language, as the main language spoken in the sending counties is a dialect belonging to the Cantonese group, which is not intelligible for individuals speaking dialects of other groups. In order to shed light on the relative importance of the two mechanisms, we also employ another measure of cultural closeness, namely a dummy variable indicating whether a firm is located in a Cantonese speaking area.

We then construct our final measure of exposure as an interaction of the two dimensions and our main analysis follows a difference-in-difference framework at the county-industry level, where we control for county and industry fixed effects.

Our main data set is the Annual Survey of Industrial Enterprises from the year 2004 conducted by the China's National Bureau of Statistics for the province Guangdong. The survey covers all manufacturing enterprises with output larger than 5 million RMB, which in Guangdong amounts to around 34,500 firms. The data set provides information about a number of firm variables in addition to exports. Furthermore, we have access to the Chinese Economic Census, which records employment and revenues for the universe of registered firms. We use this data set to analyse how the firm size distribution is affected and whether there were additional effects on smaller firms or firms in other sectors. Finally, we construct our measure of network exposure from U.S. census data.

The main findings indicate that more connected firms are more likely to export, and have higher export value. This means that the benefits of the ethnic network affect both the extensive and the intensive margin of trade. The effects are economically significant: for a one standard deviation increase in network exposure, the probability of exporting is about 3 percentage points higher for each of the three measures of industry network, and the value of exports conditional on the firm being an exporter is about 6 to 14 percent higher, depending on the measure of network exposure.

We conduct a number of exercises to investigate which -direct and indirect- channels may be driving our results. The literature has proposed two channels through which ethnic networks can directly impact exporting behaviour. Firstly, when formal contract enforcement mechanisms are weak or non-existent, ethnic networks can overcome this void through collective punishment, thus facilitating trade. Secondly, ethnic networks can overcome important information barriers that potential exporters face, such as lack of knowledge about the tastes of consumers in the destination market or play an important role in matching buyers and sellers. Moreover, ethnic networks can have indirect effects on exports through aiding the spread of technological knowledge or through promoting foreign direct investment.

We find little evidence that exports are driven by technological knowledge flows that are aided by the network, as profitability does not increase nor is the effect larger for high-tech firms. We do, however, find a positive effect on labour productivity for smaller manufacturing firms, which could be indicative of knowledge flows playing a role for this subset. Similarly, while foreign direct investment does seem to increase with exposure to the network, it cannot explain our results.

Concerning the direct channels, we further investigate whether the results can be explained by improvements in contract enforcement or by the flow of information through the network. Following Rauch (1999), we study whether the effect is driven by differentiated goods, for which the information channel should be of greater importance. We do find a larger effect for differentiated goods, supporting Rauch (2001)'s finding, that the information channel is of particular importance.

Finally, we also find effects on other firm-level variables: More connected firms have higher output and profits but lower domestic sales. They also have significantly higher fixed assets and capital, while keeping the total number of workers constant. Firms with more exposure to the network also have a higher share of workers with a university degree, pay higher wages and have higher management expenses.

While these findings are consistent with a number of hypotheses, one possibility is that ethnic networks lower informational barriers, which then allows firms to specialise in products for the U.S. market that are not demanded by Chinese consumers. Therefore, these firms sell less in the domestic market but exports are increased. The fact that more connected firms employ more high-skilled workers and more fixed assets is consistent with quality upgrading of the main product, which is in higher demand in the American market.

Our contribution is twofold. Firstly, we estimate the effect of ethnic networks on international trade at the firm level. To the best of our knowledge, our paper is the first to distinguish between the effects of ethnic networks on the intensive and extensive margin of trade at firm level. Moreover, we have access to a rich data set of firm level variables, which allows us identify the channels though which ethnic networks affect trade.

Secondly, our identification strategy captures the effects of an ethnic network formed through historic migration. Other papers have measured ethnic networks with past migration patterns (Kerr and Lincoln, 2010; Kerr, 2013; Griffith et al., 2006; Parsons et al., 2014) to mitigate reverse causality concerns. However, our very narrow definition of network allows us to further overcome the possibility that recent migrants may selectively settle in U.S. counties that have a high prevalence of industries which are well performing in China.

The paper is organized as follows: section 3.2 describes the related literature; section 3.3 outlines the mechanisms through which ethnic networks can affect international trade; section 3.4 provides an overview of the migration of Cantonese people to the U.S.; section 3.5 describes the data sources and how we construct the data sets; section 3.6 describes in detail the empirical strategy. We illustrate the results regarding exports and other firm variables in sections 3.7 and 3.8, and finally section 3.9 concludes.

## 3.2 Related Literature

This work relates to several strands of literature, which analyse the effect of ethnic networks on several aspects of the economy: international trade, labour markets, knowledge diffusion and innovation, and firm growth in developing countries. Moreover, it relates to the literature on the impact of language and culture on international trade.

Firstly, it contributes to the literature on the role of co-ethnic networks on international trade. Rauch and Trindade (2002) are among the first to empirically document the role of Chinese ethnic networks in international trade in a cross country study; they find a higher volume of bilateral trade among China and countries with a higher share of ethnic Chinese population. Rauch (2001) provides a review of the literature on the effect of social networks on international trade focusing mainly on two channels: reduction of information barriers and better contract enforcement. A closely related paper in terms of research question and empirical strategy is the recent contribution by Parsons et al. (2014): the authors use a natural experiment - the migration of the Vietnamese Boat People to the U.S. - to provide empirical evidence of a link between ethnic migrant networks and exports of American firms, thus focusing on the benefits of ethnic networks for the receiving country of migrants. Their findings establish a causal link between the geographical location of Vietnamese people in the U.S. and the volume of exports to Vietnam, suggesting that networks play a role in international trade between the two countries.

A number of papers examine the effect of networks on trade, however with a focus on the role of social networks rather than ethnic networks. Combes et al. (2005) study how migrant and business networks affect trade across French regions, measuring the latter with the number of connections between plants which belong to the same business group. Moreover, a recent cross-country study by Head et al. (2010) analyse the long term impact of countries' independence on bilateral trade with the former colonizing country and the rest of the world; they find negative effects on trade flows, and a small but positive effect on the extensive margin (i.e. probability to export) with other former colonies of the same colonizer and with the rest of the world.

The importance of migration networks in the labour market has been reviewed by Montgomery (1991) and has been the focus of a number of recent empirical papers. The work by Munshi (2003) examines their role on labour market organizations: he empirically analyses the network of Mexican migrants in the U.S. and its effect on the labour market in the destination country, by measuring the size of network as the share of individuals in the community of origin who are located in the U.S. The findings indicate that more connected individuals have higher probability of being employed and have higher wages. McKenzie and Rapoport (2007) investigate the empirical relationship between migration and wealth using data from Mexico, highlighting that migration costs decrease with the size of the migrant network originating from the same community. They find an inverse U-shaped relationship between migration and inequality in rural Mexico, and that migration contributes to decreasing inequality in sending villages with high rates of historic migration.

The role of ethnic and migrants networks has been studied in the context of knowledge and technology diffusion. Griffith et al. (2006) present evidence for the existence of knowledge spillovers across countries; with firm-level data from the U.K., they test the effect of "technology sourcing" exploiting pre-1990s technology boom location of U.K. affiliated firms in the U.S. for identification. Kerr (2008) focuses on the role of the U.S. as a frontier country in the diffusion of scientific knowledge and recognises the role of ethnic networks in knowledge transfers across countries. In a more recent paper, the same author studies the extent to which comparative advantage is an determinant of trade, using the geographic overlay of the location of past migrants communities and innovation in the U.S. to identify differences in technology diffusion and therefore comparative advantage (Kerr, 2013). Kerr and Lincoln (2010) and Moser et al. (2014) study the effect of skilled migration on innovation in the U.S., the first exploiting changes in the H-1B visa regulations to overcome endogeneity, and the latter focusing on the contribution to innovation of Jewish migrants from Germany to the U.S. at the time the Nazi party was in power.

As we explore the effect of networks not only on exports but also on other firm variables, our work also relates to the work on co-ethnic networks and firm growth. Banerjee and Munshi (2004) demonstrate that social ties of businessmen to the local community play a role in the allocation of capital, which is not necessarily in favour of the most productive firms; they show that among textile firms in Tirupur (India), those owned by locals entrepreneurs have higher fixed capital and capital intensity of production compared to firms owned by outsiders. The paper by Woodruff and Zenteno (2007) analyses the impact of the migration networks in Mexico on the development of microenterprises, and find evidence of migration networks playing a role in alleviating capital constraints in the most capital intensive industries. Another example of this literature is Nanda and Khanna (2010), which find that in India entrepreneurs rely more on ethnic networks if firms are located outside software hubs, indicating that networks are most important in environments with limited access to information and financial institutions.

Focusing on foreign direct investment (FDI), the recent work by Javorcik et al. (2011) find that the presence of migrants in the U.S. increases FDI in the country of origin, and Burchardi et al. (2016) show similar results by instrumenting ancestry composition with measures of "push" and "pull" factors, which refer to factors causing migration from a country to the U.S. and migration from all countries to a specific county in the U.S. respectively.

Besides Rauch and Trindade (2002), others have documented the role of Chinese migrant networks on many aspects of the economy. Saxenian (2002) highlights the role of first generation migrants from China and India working in the Silicon Valley, for sharing both information about technology and investment in business partnerships with their counterparts residing in their country of origin. Felbermayr and Toubal (2012) revisit the evidence found by Rauch and Trindade (2002) finding more modest effects on international trade, although still positive. Rotunno and Vézina (2012) document the importance of Chinese networks on tariff evasion, measured by the difference between exports reported by other countries and imports reported in China. Finally, Zhang and Song (2002) document the role of FDI on Chinese exports since China's open door policy.

Furthermore, our paper relates to the literature documenting the effect of culture and language on economic activities. Guiso, Sapienza and Zingales (2009) empirically estimate the role of culture, including language and genetic similarities, on bilateral trade and investment across countries. Melitz (2008) investigates the importance of a common language for international trade and finds that direct communication is more effective than having to resort to translation. Specific to the Chinese context, Chen et al. (2014) find that, although nowadays Mandarin is commonly spoken in all provinces in China, fluency in the local dialects has positive consequences on individuals' income in both services and manufacturing, and particularly in sales jobs.

## 3.3 Mechanism

Obstfeld and Rogoff (2001) have put forward the hypothesis that the trade patterns empirically observed - for instance strong border effects - indicate the presence of large non-tariff trade costs. Ethnic networks can reduce non-visible trade costs in two ways, as discussed in Rauch and Trindade (2002): Firstly, by reducing informational barriers and secondly by providing enforcement mechanisms for contracts in the presence of weak institutions. However, ethnic networks can also increase trade flows indirectly, either through increasing the flow of technology and knowledge, which makes firms more competitive in the export market, or by facilitating foreign direct investment, which in turn might increase trade, for example by allowing firms to outsource production. Finally, migrant networks could affect trade simply by changing tastes and preferences across countries. In contrast to both the direct and indirect channels, which are welfare enhancing by decreasing frictions and distortions, the latter would not necessarily imply an improvement in welfare.

Information barriers are likely to play an important role in impeding trade as has been highlighted by Rauch (2001). Firms might hold imperfect information about, for instance, the taste of foreign consumers or the products sold by foreign competitors. Obtaining this information might be an important fixed costs that impedes firms from exporting. Furthermore, such information about tastes and markets might become more costly to obtain with both geographic as well as cultural and linguistic distance. Additionally, when trading specialised or customised goods, the detailed requirements might be harder to communicate across linguistic and cultural hurdles. Ethnic migrant networks can facilitating information flow by reducing these costs, as connected individuals face lower cultural and linguistic impediments. In our case, Chinese-Americans might have a distinct advantage in communicating the preferences of American consumers and the market structure to Chinese producers. In addition networks can play an important role by acting as intermediaries and aid matching of importers and exporters. If we assume that there are search frictions due to asymmetric information, matching between exporters and importers can be costly (Ahn et al., 2011). Networks hold information about the types and trustworthiness of available producers and buyers and thus reduce search costs for their members (Rauch and Trindade, 2002).
The fact that this channel plays an important role in our setting is supported by qualitative evidence such as by Weidenbaum and Hughes (1996), who describe the role of the "bamboo network" - the ethnic Chinese networks overseas - in facilitating trade. They claim that *"[t]he leading business men know each other personally and do deals together, with information spreading through an informal network rather than through more conventional channels"*. Moreover, Kotkin (1993) writes that *"Chinese entrepreneurs remain in essence arbitrageurs, their widespread dispersion a critical means of identifying prime business opportunities"*, which indicates the importance of information flows.

The second direct channel through which ethnic networks can further trade is through enforcing informal and formal contracts. Contract enforcement may be particularly problematic in the context of international trade: Imperfections of the justice system are likely to be enlarged by distance and thus firms find it harder to enforce contracts across borders than domestically. Furthermore, contractual details are harder to pin point in the presence of geographic and linguistic barriers. Finally, in the case of international trade a large number of sunk costs may have to be paid before it can be observed whether all parties complied to the agreement. These imperfections might be particularly salient if domestic institutions are weak, such is the case in developing countries, and thus particularly relevant for China (Anderson and Marcouiller, 2002). As a result, firms are likely to rely on informal and relational contracts. Ethnic networks can play an important role in enforcing such relational contracts by providing punishment mechanisms, as has been emphasised in the seminal contributions by Greif (1989, 1993). This channel has also been described by Weidenbaum and Hughes (1996), who write that *"[i]f a business owner violates an agreement, he is blacklisted. This is far worse than being sued, because the entire Chinese network will refrain from doing business with the guilty party"*. In addition, in many cases, if the quality of a product is hard to observe, network intermediaries often are willing reduce risk for the importer by guaranteeing quality and deepening reputational concerns (Chaney, 2014).

Another channel through which ethnic networks may affect international trade, albeit indirectly, is promoting technology diffusion across countries. The relationship between ethnic networks and knowledge flows has been analysed widely in the innovation literature (Kerr, 2008; Kerr and Lincoln, 2010), though rarely in relation to exporting behaviour (an exception is Kerr (2013)). We suppose that increased technology and knowledge diffusion allows connected firms to increase their productivity or product quality through imitation or innovation. This in turn, might make firms productive enough to make exporting profitable, thus indirectly leading to an increase in exports. It is important, however, to acknowledge that there might also be a reverse effect: For example, Keller (2002, 2004) argues that trading differentiated intermediate goods, which embed innovation, facilitates technology flows across countries.

A second indirect channel through which ethnic networks can affect trade is through fostering foreign investment. This channel has been the focus of recent studies, which show that the presence of migration networks in a country increases FDI flows towards their origin country of migrants (Javorcik et al., 2011; Burchardi et al., 2016). This may happen because networks help information flow across countries, or because they enhance transactions in environments with weak institutions. High levels of FDI in turn have been hypothesised to promote international trade: Zhang and Song (2002), for example, explore this channel in the context of China, showing that increases in FDI over time can be linked to improvements in manufacturing export performance. In this way, an observed link between connectedness to the ethnic network and trade may be caused by increases in FDI.

The final mechanism highlighted in the literature is the so-called "preference channel", first discussed by Gould (1994). This channel supposes that a large migrant community in a destination country leads to an increase in trade simply by increasing the share of the population with tastes that favour goods from the sending country. We argue that this channel is less relevant in our setting, as we exploits industry-level differences in ethnic Chinese employment in the U.S. As a result, we do not capture aggregate effects caused by a large number of ethnic Cantonese from the sending counties in China in the U.S. but only differences across industries. Moreover, whereas the preference channel is generally consistent when analysing trade of differentiated and final goods (Rauch and Trindade, 2002), we explore network effects also for both intermediate and undifferentiated goods.

## 3.4 Historical Background

### 3.4.1 Emigration From China

Emigration from China has a long history starting in the 10th century with merchant emigrants building a trading network all over Southeast Asia. Mass emigration, however, only became prevalent in the middle of the 19th century. This first emigration wave started around 1842 with the loss of the first Opium War, when China was forced to open itself to Western influences. Emigration accelerated in the 1860's, when the Qing government lifted its ban on emigration, which had been imposed since the seventeenth century (Woon, 1990). By the outbreak of World War II, between 8.5 to 9 million Chinese were living outside Chinese borders all over the world from South East Asia to South and North America and Australasia. Migration only came to an abrupt halt in 1949 when the People's Republic of China was declared and the borders were closed.

During this first emigration wave, individuals emigrated mostly through informal networks in order to overcome credit and informational constraints. As a result the origin of migrants for a given destination country were extremely localised: While an estimated 90% of all emigrants during this period originated from Guangdong or Fujian (Woon, 1990), nearly all of the 19th century Chinese immigrants to the U.S. and the Kingdom of Hawaii originated from eight counties adjacent to Guangzhou. Historians estimate that 80-90% came from the Siyi districts, comprising Taishan, Xinhui, Kaiping, Heshan and Enping counties (Hsu 2000). Somewhere between 10-20% percent of immigrants came from Sanyi districts, comprised of Panyu, Nanhai and Shunde counties. These counties, which used to be seven counties at the time of emigration, are our main focus and will be referred to as the sending counties. A third, smaller group of immigrants came from Zhongshan, south of Guangzhou (for a Map of the counties see Figure 2). The migrants to mainland U.S. were mostly members of the Punti ethnic group, while those in Hawai'i were primarily Hakka (Voss and Allen, 2008). It is important to note that these counties, however, were not necessarily the ones that saw the most out-migration, but only saw the most migration *to the U.S.* Emigrants to other destination countries in South East Asia or Oceania originated from other counties. The general pattern that individuals originating from a given county migrated to the same country seemed to hold all over southern China (Voss and Allen, 2008).

Emigration was motivated by push-factors, such as overpopulation, and by the political instability that was spreading all over China, which caused the Taiping and the Boxer rebellions and the more localised Punti-Hakka Clan Wars, which culminated in around a million casualties. The two provinces in general, and the sending counties in particular, were some of the areas most characterised by over-population and food shortages, which were exacerbated by droughts and floods throughout the 19th century.

At the same time, there were a number of "treaty ports" established in both provinces, the most notable being Guangzhou (Kanton) in Guangdong. Treaty ports were ports ceded by the Qing dynasty to a number of Western powers as well as Russia and Japan after the Opium wars, where free trade was allowed to take place. Thus shipping routes from these locations were already established (Faure and Siu, 1995).

The reasons why emigrant to the U.S. originated nearly exclusively from the sending counties are not well documented. The initial pattern could have originated because of the proximity to Guangzhou and Hong Kong, which were the main shipping destinations from San Fransisco. Initial patterns of migrations were likely to be predictive of future migration due to the need of a network in the destination country, coupled with the linguistically and culturally diverse landscape of Guangdong; the latter implied that individuals of the same linguistic group could benefit from a particularly close knit network, which others could not have accessed. Furthermore, the fact that emigration was banned until the end of the century could have contributed to informal networks being of particular importance.

Table B.1 shows the number of Chinese migrants that arrived in Canada. As migrants from China arrived to the entirety of North America nearly exclusively via San Francisco, immigrants to Canada have the same origin as immigrants to the U.S. The data has been assembled by Yu (2011) using the Canadian Head Tax records from 1885 to 1949 and covers almost 100,000 individuals of Chinese origin. While such data exists for the U.S., to the best of our knowledge it has not been digitalised and made available. The Table shows that the sending counties identified above constitute around 98.3% of all the Canadian-Chinese in the sample.

### 3.4.2 Ethnic-Chinese in America

At the beginning of the first migration wave during the 19th century, the main pull factor was the gold rush. Like many Europeans, Chinese emigrants were drawn to the U.S. in the hope to make their fortunes extracting gold. Therefore, and for geographic convenience, most early Chinese immigrants settled in California. Later Chinese immigration was encouraged in order to provide labour for the construction of the Transcontinental Railway, as well as to a limited degree to replace former slaves in the southern plantations. By 1882, around 380 000 Chinese left China and settled in mainland U.S. and a further 46 000 settled in Hawaii (Voss and Allen, 2008).

The mass migration came to a stop because of the Chinese Exclusion Act in 1882, which was subsequently extended under the name of Geary Act in 1892. It was the first major law that restricted immigration to the US and is seen a response to anti-Chinese sentiments that started from California, and then spread in the whole country, during the second half of the 19th century.

The act prohibited migration of Chinese *"skilled and unskilled labourers and Chinese employed in mining"*, under penalty of imprisonment or deportation. Effectively, however, it impeded all kinds of Chinese migration, as it was hard for migrants to prove their intentions of not become labourers. There were few exceptions, for instance for wealthy merchants or students. Further State laws forbade interracial marriages, limited civil rights and restricted the possibility of employment by non-Chinese. Following the Act, more laws restricting migration were approved, until the National Origins Act of 1929, which capped immigration to 150,000 people per year and prohibited all immigration from Asia. It also prohibited Chinese from becoming U.S. citizens. In addition, other legislation excluded the Chinese from certain occupations, especially in California, which for example barred Chinese form owning property, testifying in court or for Chinese children to attend schools. The situation only improved with the repeal of the Exclusion Act in 1943, motivated in part by the alliance between China and the U.S. during World War II (Lee, 2003).

Upon their arrival, the ethnic Chinese had mostly settled in Chinatowns, among which the largest were in San Francisco and New York. Due to discrimination, the Chinese continued predominantly to live within the borders of the Chinatowns. Before 1950, the American Chinese like most other Asian-Americans, were employed in rural farmwork or in service jobs such as launderettes or restaurants (Hing, 1993) Figure 3.1 shows Chinese settlements in the U.S. in 1890 on the left, just after the Act was passed, compared to the location of Chinese people in 2000. Although the numbers are much larger in 2000, the Chinese nowadays are concentrated in the similar areas as the early migrants.

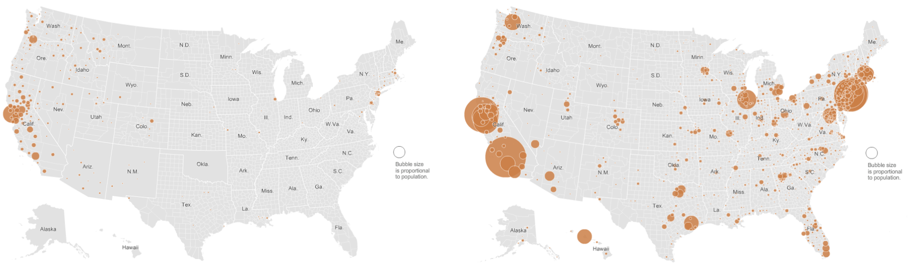

Figure 3.1: Chinese Settlements in the U.S. in 1890 and in 2000

Even after the abolition of the Exclusion Act, the number of Chinese migrants was limited predominantly to family reunification and to 105 persons per year (Zhao, 2002). Large-scale Chinese immigration did not occur until 1965 when the Immigration and Nationality Act of 1965 lifted national origin quotas (Hing, 1993). The 2004 United States Census reports over 2.8 million Chinese in the United States, about 1% of the total population and 23% of the Asian population.

## 3.5 Data Sources and Summary Statistics

In this section we briefly outline the main data sources and provide some summary statistics.

### 3.5.1 Firm information

We have access to two data sets containing firm data in Guangdong. Firstly, the Annual Survey of Industrial Enterprises of 2004, which is a survey of all large manufacturing firms. Secondly, the Chinese Economic Census of the same year, which includes all registered enterprises, but only minimal information about each firm. We use the first data set for our main analysis as it includes information on exports, while we use the second data set to analyse spill-over and direct effects on small firms and for industries other than manufacturing.

The Annual Survey of Industrial Enterprises is an annual survey conducted by the China's National Bureau of Statistics. It collects information about all state-owned firms and all privately owned firms with revenues higher than 5 million RMB in the manufacturing sector. This also includes firms that are partially or fully foreign owned. Overall, around 5% of all firms in our sample are state owned, while around 12% are at least partially foreign owned. Our data set covers the Guangdong province only. We exclude state owned firms from our analysis, as their operation is generally regarded to be fundamentally different and access to the overseas Chinese network less important than for private firms.

The data set is very detailed in terms of firm-level variables observed. The main variable of interest is the value of total exports measured in thousands of RMB. We create two variables from this information: Firstly, a dummy variable indicating firms' export status; secondly, the log of export value. Around half of the firms in our sample are exporters. While this is a much higher share compared to other data sets (Bernard et al. (2009) for example find that in 2000 only 3.1% of all U.S. firms export), it is important to keep in mind that this is foremost driven by the fact that our sample only includes large firms. Furthermore, Guangdong is one of the main exporting regions of China, and thus we would expect the share of exporters to be large. Unfortunately we do not have firm-level information on bilateral trade between China and the U.S.; thus as a robustness check we weigh reported exports by the average share of a given Chinese industry's total exports that is purchased by U.S. firms[1].

Other variables of interest for our analysis are: 4-digit Chinese Standard Industry Classification, total number of workers employed, capital by origin (domestic, foreign, state), profits, wages, age of the firm, R&D expenses and management expenses. We further calculate TFPR, as described in section B.1.

Table B.2 shows some summary statistics of key variables in our sample. We show the summary statistics for the entire sample and for exporting firms separately. Regarding the whole sample, as mentioned previously, slightly less than 50% of all firms are exporting. Around 5% of the sample is state-owned and 10% of total capital is provided from foreign sources. In terms of employment, the average firm is medium sized, with 289 workers.

Comparing exporting and non-exporting firms, we find similarly to the general literature that exporting firms are significantly larger than

[1]For more details see section 3.7.2, which describes the robustness checks

non-exporters in terms of the number of workers, total wages paid and output. They have slightly more capital in total and fixed assets. They are, however, less likely to be state owned and have a smaller share of foreign owned capital. Furthermore, the average share of high-skilled workers is lower.

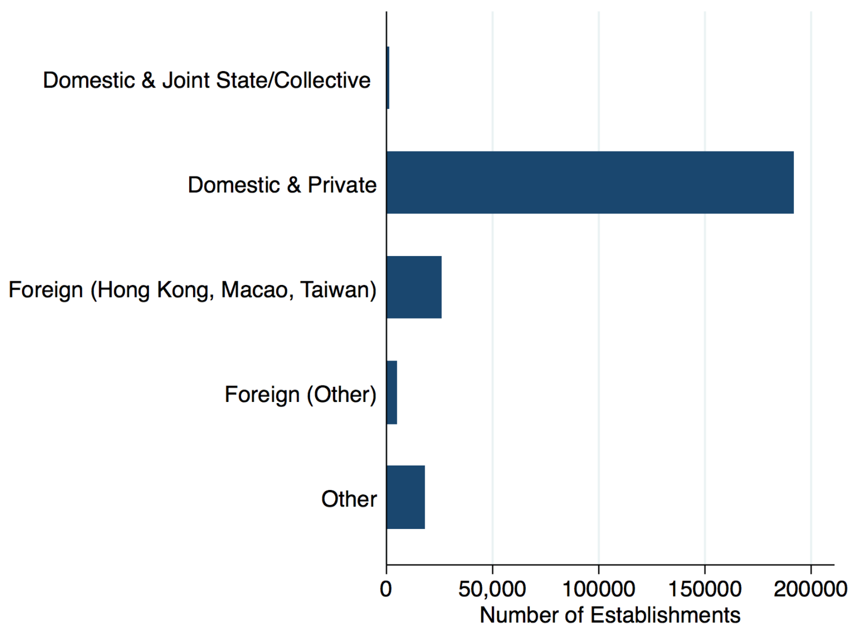


Figure 3.2: Distribution of Firms According to Ownership

**Notes:** Data from the 2004 Chinese Economic Census.

### 3.5.2 Cultural Exposure Measure

In this work, we are investigating the effect of having better access to the American-Cantonese network, which was formed in the late 19th and early 20th century. Our main measure of access to the American-Cantonese network measures whether the firm is located in one of the sending counties. As explained in section 3.4.1, this network's native language is two subgroups of the Cantonese language group: Siyi and Sanyi. Therefore, we use whether a firm is located in a Cantonese speaking county as a robustness check. Figure 3.3 shows the geographical distribution of both the two dialects of interest (Siyi and Sanyi) as well as the distribution of Cantonese.

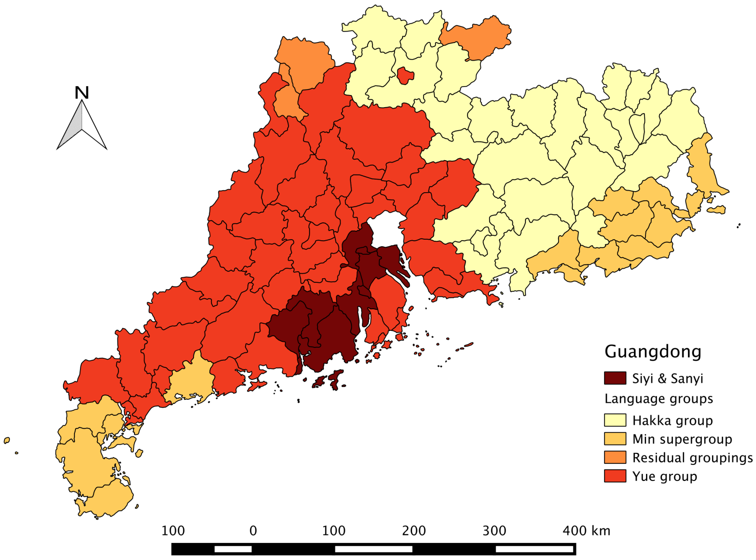


Figure 3.3: Distribution of Languages in Guangdong

**Notes:** Data from Lavely (2001).

The information about language distribution in Southern China is obtained from a coding scheme developed on the basis of the *Language Atlas of China*, which was compiled jointly by the Australian Academy of the Humanities and the Chinese Academy of Social Sciences in 1987. The data we use in this paper has been encoded by Lavely (2001) at the county level, such that it provides for each county on the Chinese mainland the five most widely spoken language groups and sub-groups.

### 3.5.3 Industry Exposure: Cantonese Workers by Industry in the US

We obtain the data on the number of workers Cantonese from the 5 percent sample of the 2000 Population Census, which gives us information at the four digit industry level. We consider only workers who claim to be of Cantonese origin, speak Cantonese at home and were not born in China. We impose the first two restrictions to accurately measure the network that we are interested in, i.e. the descendants of the early

Cantonese migrants in the late 19th and early 20th century. Further, we exclude individuals who were born in China in order to mitigate the endogeneity concerns caused by possible selective settlements of more recent migrants. This means that we reduce the possibility that our effects are driven by Cantonese workers moving to the U.S. in order to work in industry that are particularly strong in their place of origin in China. Note that we use the absolute number of workers and not percentages, because of aim is to capture the probability that a given firm in industry i that has access to the Cantonese network has at least one contact in the same (or downstream) industry.

Figure 3.4 shows the number of Cantonese workers across industrial sectors according to the U.S. census 2000 industry classification. The Cantonese workers are distributed across a wide range of sectors. The sectors with the largest number of Cantonese workers are education, health and social services, manufacturing, professional services and retail trade, while relatively few Cantonese work in fishing, mining, utilities and the armed forces.

Tables B.4 and B.5 show the ten 6 digit NAICS industries with the highest and lowest number of Cantonese workers. Table B.4 reassures us that we are capturing a wide range of industries, which employ both high skill workers (e.g. in universities, IT related manufacturing and services) as well as low skill workers (e.g. in restaurants, grocery stores).

Our measure is likely to be relevant with regards to all of the channels discussed above. Firstly, a larger number of Cantonese workers in a related industry may lower the information costs related to exporting by providing specific information regarding the market for a given product. This information is likely to be available to a large number of workers within an industry. Secondly, the workers may be possible points of contacts to share tactical knowledge and thus allow Chinese firms to learn about production techniques. This channel, however, should only be present when using the number of workers in the *same* industry. The third channel through which networks can increase trade is through improving contract enforcement. We should be capturing this particular channel if the Cantonese workers are in a higher management position. We therefore investigate whether our measure correlates with he number of Cantonese in management positions. However, even a large num-

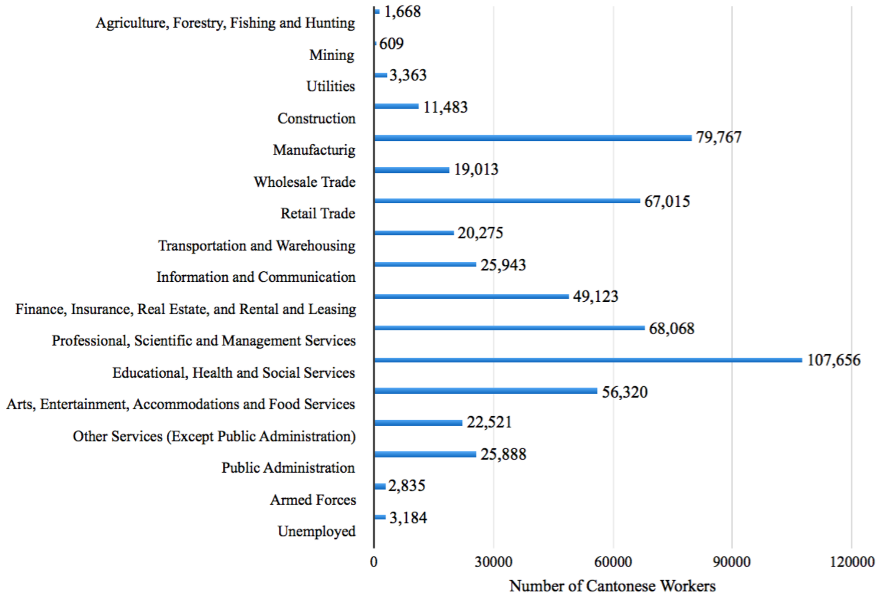


Figure 3.4: Distribution of Cantonese Workers Across Sectors

**Notes:** This graph shows the distribution of ethnic Cantonese workers by sector in the U.S. in 2000. Data from the U.S. Census.

ber of lower level Cantonese workers may improve contract enforcement by improving communications and thus increasing the contractability of a given transaction. However, we regress our measure of Cantonese workers on the number of Cantonese Workers that are self-employed, as unfortunately, we do not have information on whether an individual is in a management position. The correlation can be seen in Figures B.1 and B.1.

## 3.6 Empirical Strategy

Our empirical strategy exploits the interaction between two measures of network exposure, one at the industry level and the other at the geographic level.

The treatment variable for all regressions is *network exposure*, which measures the exposure or access of each firm to the network of overseas ethnic Cantonese in the United States at the county industry level. In our framework, a firm can be potentially connected along two dimensions: an industry dimension and a cultural dimension. Thus our final measure is the interaction of industry exposure and cultural exposure:

$$network\,exposure_{i,c} = industry\ exposure_i \times cultural\ exposure_c \qquad (3.1)$$

where $i$ stands for four-digit industry and $c$ stands for Chinese county. Firms are grouped according to the Chinese industry classification system. In China, counties are the third level of administrative divisions, after provinces and prefectures. As of September 2016, there are 2,852 county divisions. In our data set we observe firms in all 123 counties in Guangdong.

### 3.6.1 Industry Exposure

*Industry exposure* captures the degree of exposure of a Chinese firm to its ethnic network in the U.S. We analyse three ways in which a Chinese firm is linked to a U.S. industry.

Firstly, we analyse the link between Chinese manufacturing firms and related retailers and wholesalers in the U.S. We assume that, if a Chinese firm in Guangdong operates in an industry that produces, say, leather jackets, it is likely to be more exposed to the network if more workers of Cantonese origin (as the early migrants to the U.S.) work in an industry that sells leather jackets. Thus, if ethnic networks do increase exports for Chinese firms a major effect should be seen between manufacturing firms in China and wholesale and retail firms of the same products in the U.S. We measure this effect by calculating the number of workers of Cantonese origin in the U.S. that work in wholesale and retail industries which are likely to sell products manufactured by Cantonese or Chinese firms:

$$industry\,exposure\,retail_i = number\,of\,Cantonese\,workers_j$$

where $i$ denotes the main 4-digit industry in which a Chinese firm operates and $j$ is a retail or wholesale industry in the U.S. who is likely to buy the final goods produced by industry $i$.

Secondly, we analyse the link between Chinese firms and related downstream manufacturing industries in the U.S. These are manufacturing industries which use goods of the same category as the ones produced by Chinese firms in their manufacturing process, and are therefore potential buyers of their products. To illustrate the relation of this specific type of network to exports with our previous example, we assume here that a producer of raw or processed leather in China benefits more from the network if more ethnic Cantonese in the U.S. are employed in industries that use leather for production. We measure the effect of this specific network with the number of workers that are employed in related downstream manufacturing industries, which are likely to purchase products such as those produced by the Chinese firm. This measure is calculated as follows:

$$industry\,exposure\,manufacturing_i = number\,of\,Cantonese\,workers_k$$

where $k$ is 4-digit a industry in the U.S. which uses the category of goods produced by industry $i$ in its manufacturing process.

The third measure of industry-level network which we analyse measures the potential benefits for exports of being more connected to the same industry in the U.S. A Chinese firm is considered more connected to its ethnic network if it operates in a four-digit industry that employs a larger number of ethnically Cantonese workers in the U.S. Specifically, this is calculated as:

$$industry\,exposure\,same\,industry_i = number\,of\,Cantonese\,workers_i.$$

In summary, the three definitions of ethnic network exposure at the industry level capture different effects. The first and the second measure have a direct effect on exports: they focus on the importance of networks in order to sell goods to a foreign country. However, the effect of the third measure, which computes exposure to ethnic networks within the same industry, is both direct and indirect; the indirect effect is related to the fact that networks flowing along the same industry may help knowledge and technology flow to firms across countries. Note that the three different definitions of industry exposure to the Cantonese ethnic network may not necessarily be defined for the same number of industries, as firm may operate in an industry which includes only final goods, or only intermediate goods. Conversely, an firm can operate in an industry which includes both intermediate and final goods.

### 3.6.2 Cultural Exposure

The other dimension according to which a firm can be connected is its cultural similarity with the network of ethnic Cantonese workers in the U.S. This relies on the assumption that a firm located in a county in China whose population shares close cultural ties with early immigrants in the U.S. has better access to the American Chinese network.

To identify cultural closeness, we exploit the fact that the emigration to the U.S. until the 1980's was extremely localised around the southern coast of Guangdong, whose population mainly spoke, and still speaks, a particular dialect of Cantonese.[2] We define *cultural exposure* as a dummy variable indicating whether a firm is located in one of the sending counties of migrants to the U.S. in the 19th century.

With this measure of cultural exposure we are aiming at estimating the effect of both language similarity and kinship ties. It captures the effect of language because the linguistic landscape of South China is very diverse, such that even within few kilometres the local dialects are mutually unintelligible; therefore speaking the same or a similar language as the diaspora communities can improve the interaction between the two different groups. While nowadays communication between mainland Chinese of all areas of origin is facilitated by the near universal knowledge of Mandarin Chinese, many American-Cantonese emigrated before the teaching of Mandarin became widespread.[3]

In addition, our measure captures the effect of networks devel-

[2]Sections 4.1 and 3.5.2 give a detailed overview of the migration wave from Guangdong to the U.S. and the language landscape in Guangdong.

[3]That language still plays an important role in China today is demonstrated by for example Chen et al. (2014), who show that immigrants in Shanghai that are more likely to speak and understand the local dialect are more successful on a number of dimensions: for example they are more likely to be self-employed and have higher hourly earnings.

oped through kinship ties because we focus on the exact counties where the early migrants to the U.S. originated from. Even after generations, it is possible that early migrants will still have ties with the relatives left behind in China. Moreover, anecdotal evidence shows that family ties are still an important component of ethnic networks, particularly in China (Gomez and Cheung, 2009).

As a robustness check, we use an alternative measure of cultural exposure: a dummy variable indicating whether a Chinese firm is located in a county where the main language spoken is Cantonese. Comparing the results when using these two different measures can shed some light on the relative importance of language versus kinship ties for international trade.

Table B.3 shows the average exposure to our three measures at the industry level as well as the cultural exposure to the network.

### 3.6.3 Difference-in-Difference Regression

We run difference-in-difference style regressions with a continuous variable (industry exposure) interacted with a dummy variable (cultural exposure) of the following form:

$$y_{f,i,c} = \beta_0 + \beta_1 network\, exposure_{i,c} + \beta_2 age_{f,i,c} + \theta_i + \pi_c + \epsilon_{f,i,c} \qquad (3.2)$$

where $y$ is a firm-level outcome of interest, *age* indicates the age of the firm, $\theta$ and $\pi$ are four-digit industry and Chinese county fixed effects. As our specification does not allow to control for industry-county fixed effects, we interact county controls with industry fixed effects as a robustness check, where the county controls included are dummy variables indicating whether average education, migration and total population of the individual counties are below (=0) or above (=1) median.

For most of our analysis we restrict to privately owned, domestic firms, but we also investigate how results change when we do not apply these restrictions: we run robustness checks where we include foreign owned firms, controlling for the amount of foreign capital of each firm. We cluster standard errors at the four-digit industry level, according to the Chinese industry classification. It should be noted that throughout the whole analysis we rely on cross-sectional data, as we have firm level information about Chinese firms in year 2004 only.

Note that both the industry and the geographic exposure, if interpreted individually, might be endogenous; thus, we focus on their interaction. As we essentially conduct a difference-in-difference analysis across industries and counties with different levels of exposure, our identifying assumption is that industries in China do not differ systematically across Cantonese and non-Cantonese speaking areas.

Although we analyse the effect of the Cantonese network on exports, there may be network effects on imports from the U.S. to China as well. We focus on exports rather than on bilateral trade mainly because our data set does not contain firm level information about imports. However, it is important to note that the effect of the ethnic networks may be larger when considering bilateral trade rather than focusing on exports only.

### 3.6.4 Identification Concerns

Despite being a single cross-section, our identification strategy basically functions similar to a difference-in-difference strategy with continuous treatment intensity, as we difference across more affected industries and across treated and non-treated counties. In a classic difference-in-difference, the key identifying assumption is the so-called *parallel trends assumption*, i.e. that in the absence of treatment, the treated group would have exhibited the same changes over time as the untreated group. Our equivalent is that industry-specific effects are the same in treated counties as in non-treated counties. This might be violated if sending counties have different characteristics compared to the other counties in the province, or even compared to other counties within the Cantonese speaking area. Unfortunately, we cannot provide support for this assumption as is possible in the classic difference-in-difference setting, where one analyses time-trends before treatment. This is not possible in our case, as all industries are affected. We try to mitigate some concerns regarding this assumption by including county-level controls and interacting these with industry level fixed effects. This would for example mitigate the concern that sending counties are more or less educated and industries that benefit from a more educated work-force also happen to be more connected. However, there is a limit to controls we can include and there might be unobservable factors that might be driving our results.

The identification strategy may give rise to further concerns related to the potential endogeneity of the network we estimate. Firstly, endogeneity may occur if more recent migrants decide to migrate to the U.S. to work in specific industries. This could occur if ethnic Cantonese migrants connected to certain industries decided to move to the U.S. in order to create export possibilities. As a result, those recent migrants would most likely work in the same industry, or related related downstream industries, in the U.S.

While this is a potential issue, we mitigate the selective migration problem by excluding from our measure of industry exposure those ethnic Cantonese workers who are not born in the U.S. Given that emigration from China to the U.S. in recent times was very limited between 1949 and 1977, this strategy should rule out most of the recent migrants.

A further concern is that our result may be driven by non-random allocation of Cantonese workers across industries due to ethnic Cantonese people being skilled in particular industries; for this reason, these industries would thrive in both countries. If one assumes that those skills can persist for several generations, this potential issue would be stronger for the measure of industry network exposure based on Cantonese workers in the same industry rather than for the two other measures, which are based on connections across industries. Moreover, if this were happening our estimates are likely to be biased downwards, as part of the control group (the Cantonese speaking counties) would be affected by the network. As an indirect test, we estimate equation (3.4) restricting the sample to firms located in Cantonese counties, thus comparing the sending counties to other counties within the Cantonese area of Guangdong. Moreover, adding Chinese county controls interacted with fixed effects should to some extent take care of county-specific factors affecting exports in different industries.

One remaining concern is the possibility that American firms choose to hire ethnic Cantonese workers because of the influence, or pressure, of their already existing trading partners in the sending counties or in Cantonese areas, because of their kinship ties with Cantonese workers in the U.S. In this case, we would still be capturing a network effect, but with reverse causality: overseas networks in China would affect the hiring choices of American firms in related industries. Although we cannot completely rule out this concern, it is unlikely that this channel would explain the entire differential in export flow from Cantonese firms to the U.S.

A further concern is that the province of Guangdong hosts a number "special economic zones" which are aimed at promoting trade; one of this is the largest city and port, Guangzhou. Although potential differences cannot be excluded, it is important to note that none of the special economic zones are located within the sending counties. Moreover, the county of Guangzhou is excluded from the analysis.

In this section we describe the main results, obtained by estimating equation (3.4). Table B.6 shows the results when regressing export status on the three different measures of network exposure, estimated with linear probability model. Columns 1, 3 and 5, show the estimates without Chinese county and 4-digit industry fixed effects; we include them in columns 2, 4 and 6. For the variables measuring network and industry exposure, we report coefficients indicating the average increase in the dependent variable corresponding to a one standard deviation increase in the independent variable. First, notice that industry exposure, whether measured as the number of Cantonese workers in related retail, downstream manufacturing or same industry, is positively correlated with the probability of the firm being an exporter. Being located in one of the sending counties of migrants, however, is associated with a 17-18 percentage point decrease in the probability of exporting, which reflects underlying differences in factors affecting firms' export status across counties. However, we are mainly interested in the coefficients of the network exposure variables, which we define as the interaction of the two dimensions.

All of our measures of ethnic network exposure have a positive and significant effect on the probability of exporting. With fixed effects, a one standard deviation increase in exposure to retail and wholesale network is associated with a 2.9 percentage point increase in the probability of being an exporter, whereas exposure to downstream manufacturing network and same industry network are both associated with a 3 percentage point increase.[4]

Similarly, Table B.10 shows the results on export value conditional on being an exporter. Here our measures of industry exposure are not consistently positive and significant, but being located in one of the sending counties always has a large negative effect on export value. The interaction of the two measures is positive and significant across all specifications except column 5 (without fixed effects), and the effects are large: they range from the 5.7% increase in export value with a one standard deviation increase in exposure to downstream manufacturing network, to 13.8% for the retail and wholesale network. In Table B.7 we repeat the exercise above, clustering standard errors at the county instead of the industry level. Reassuringly, results remain robust.

These results indicate that firms having access to a larger network in the U.S. can gain positive effects in terms of trade, both at the extensive and the intensive margin.

## 3.7 Results: Exports

### 3.7.1 Baseline Results

### 3.7.2 Robustness

In this section we present a set of robustness checks and additional results regarding exports.

Firstly, we explore how the results are affected when we measure cultural exposure including all counties where the most widely spoken language is Cantonese, instead of only the sending counties. Table B.8 shows the results: both the retail and downstream manufacturing network have a positive effect, whereas the effect of the same industry network is not statistically different from zero. The magnitude of the effect is smaller, which suggests a stronger effect of the network in the sending counties compared to other Cantonese counties.

[4]Note that when estimating equation (3.4) with industry and county fixed effects, the coefficients of the variables *industry exposure* and *cultural exposure* are not estimated, as they vary at the industry and county level respectively.

Furthermore, we analyse the presence of heterogeneous effects for firms located in the sending counties compared to firms in the Cantonese speaking part of Guangdong. We conduct this exercise for two reasons. Firstly, to address the identification concern that our results are driven by ethnic Cantonese having a comparative advantage in certain economic activities, due to human capital formation or preferences. Secondly, this allows us to distinguish whether the main driver of the results is the ethnic and linguistic similarity, which would be shared by all ethnic Cantonese, or kinship ties, which would only link the American-Cantonese to the sending counties. The results are shown in Table B.11. We are able to test for heterogeneous effects by including in one regression the two network exposure variables, calculated with the measure of cultural exposure being either a Cantonese or a sending county dummy. Note that as the sending counties are all within the Cantonese speaking part of Guangdong, the network exposure variable constructed with the sending county dummy captures the differential effect. The results show that the differential effect for firms in the sending counties is always positive and significant, which indicates that firms located there benefit additionally from the network compared to the other Cantonese firms. We do however, also find a positive effect for firms in Cantonese counties for two of the network measures (downstream manufacturing and related retail and wholesale industries), though smaller in magnitude. This suggests that firms sharing a similar language and ethnicity with the U.S. network can experience beneficial effects even in the absence of close kinship ties.

The possibility that industry-specific skills of ethnic Cantonese (or of people originating from the sending counties) might drive the results would be further reduced if we could include industry-county fixed effects in our regressions; these would capture specific effects of each industry within a county. Although our specification does not allow it, we control for county characteristics interacted with industry fixed effects. The results are shown in Table B.9, and they indicate that Chinese county characteristics are not driving our results: the size of the coefficient is larger compared to the baseline specification.

The export data at the firm level measures total value of exports; we do not have information about the destination of those goods. In order to have a more precise estimate of how networks affect export to the U.S., rather than to any country, we weigh export value of each firm by the share of its industry's exports to the U.S. out of total industry exports. We would expect larger coefficients if those industries which are more connected according to our industry exposure variable also sell a larger share of the total exports to the U.S., because the export value of firms in those industries would be multiplied by a larger share. The results of these regressions are show in Table B.13 Note that the coefficients are positive and significant, and they are also larger in magnitude compared to the baseline specification (columns 1, 3 and 5) and compared to Table B.9 (columns 2, 4 and 6).

We address one additional concern, namely the possibility that our measures of industry exposure identify spurious relationships rather than network effects. This would occur if larger industries were also employing a higher number of Cantonese workers; therefore the higher trade flows would be a result of the size of the industry, and not of the network. To tackle this issue we control for the number of total workers by industry (net of the ethnic Cantonese) interacted with cultural exposure. Table B.14 shows the results: the coefficients on our ethnic network exposure variables remain positive and statistically significant, with the exception of the effect of the retail network on the extensive margin, which is not statistically significant at the conventional levels (the p-value is .101).

Finally, we analyse foreign firms further by examining the effect of networks only on exports of foreign owned firms. Table B.19 shows that networks increase the value of exports and leave the probability of exporting unaffected. The size of coefficients for all three measures (larger than those for domestic firms) indicates a potential effect of foreign investment on the intensive margin; however, there does not seem to be an effect on the extensive margin. This suggests that foreign investment does not help overcoming fixed costs associated with trade, which should predominantly affect the probability of exporting.

### 3.7.3 Channels

**Information vs. Contract Enforcement**

As discussed in section 3.3, ethnic networks can facilitate trade by reducing information barriers or by improving contract enforcement. In order to further identify the relevant channels at play, we conduct the exercise suggested by Rauch and Trindade (2002) and investigate whether there are heterogeneous effects for differentiated goods. Rauch and Trindade (2002) distinguish between differentiated goods and goods with a reference price or that are traded on central markets. They argue that informational barriers should play a more important role for the decision to export differentiated goods, as for these goods - in contrast to the reference priced goods - the price is not a sufficient indication of the profitability of exporting. Networks might reduce informational barriers by sharing knowledge about consumer tastes or by matching buyers and sellers, both of which are more difficult to ascertain for Chinese firms in the case of differentiated goods. On the other hand, they claim that contract enforcement barriers should have the same role for both types of goods. Rauch and Trindade (2002) do, however, admit that there is an important caveat to this approach: the complex nature of differentiated goods means that aspects such as quality might be non-contractible. Thus the ethnic network might play a bigger role by ensuring that informal contracts are enforced. Furthermore, particularly in the intermediate goods sector, differentiated goods are more likely to be customised for each buyer and therefore hold-up problems are more severe.

We use the classification published by Rauch (1999) to identify industries that produce differentiated products; for our analysis we choose the most conservative classification. Table B.15 shows the results for the three measures of network exposure on both the probability of exporting and the value of exports. Column (1) shows that in related retail industries, the effect of network exposure on the probability of exporting is driven by differentiated goods. However, we do not find such differential effect on the value of exports in column (4). In the case of exposure to the same industry network a similar pattern can be discerned (columns (3) and (6)). However, when we consider the network of downstream manufacturing firms, we observe the opposite pattern, i.e. no additional effect on the probability of exporting, but a large positive additional effect on the value of exports of around 3.6%. These findings indicate that overall there is a larger effect for differentiated goods, suggesting that the information channel may play a dominant role.

This is further supported by the fact that we find a similarly sized effect for all three measures of network exposure. In fact, while information could flow equally through the network in downstream manufacturing, related retail and wholesale industries as well as the same industry, the network in downstream industries (retail and manufacturing) should have a stronger effect if contract enforcement issues are driving our results. The fact that we find no such difference supports the interpretation of information flows being a main driver of the results.

To further investigate whether contract enforcement plays an important role by analysing whether results differ if we use instead of the number of total workers in an industry, the number of self-employed workers and the number of wage workers in an industry to construct our measures of exposure. The idea behind this is that if contract enforcement is the main channel through which the network works, we should see a stronger effect when concentrating on the self-employed workers. The number of self-employed workers should matter more for contract enforcement, as these workers would have the power to sign contracts and thus interact directly with firms in China. We concentrate on the number of workers in related retail and downstream manufacturing industries, as the network in the same industry should not facilitate contract enforcement. These results are presented in Table **??**. The coefficients for self-employed and wage workers are remarkably similar indicating that it contract enforcement is not the main driver of our results. Instead the results point towards facilitating information flows being the main channel, as for this channel the position of the workers is less important.

### Technological Knowledge Flows

Another channel highlighted in the literature is that networks facilitate the flow of technological knowledge. While this is clearly related to what we referred to as "information flows" in section 3.7.3, it has been often regarded as a separate channel, as it focuses on information about technology and production processes that could be more easily shared through the network. Even though technological knowledge is not directly related to trade, it could nevertheless be an important driver of our results.

We investigate this channel in two ways. We firstly analyse directly the effect of network exposure on total factor profitability (TFPR), which is the product of prices and total factor productivity (TFP). The rationale is the following: If technological knowledge is being transmitted from the U.S. to China, we should see a positive effect on firms' TFP. Although we do not observe this directly, as long as prices do not decrease more for exposed firms, this positive effect should translate into a higher TFPR. Table B.17 shows the results for all domestic firms, as well as for exporting and non-exporting firms. Columns (1) to (3) show that neither of our three measures of network exposure have a significant effect on profitability. As industry-specific technological knowledge flows are likely to be most affected by access to the overseas Chinese network in the *same* industry, we would expect this measure to have a larger effect. However, column (3) shows no significant effect. When analysing exporting and non-exporting firms separately (columns (5) and (6)), we find instead that average TFPR is decreased for exporting firms with greater access to the network in downstream manufacturing industries and in the same industry; the corresponding effects on TFPR are 1.6% and 2.0%. The coefficients for non-exporting firms are positive but not statistically significant. While these results seem counter-intuitive, they are consistent with the hypothesis that networks decrease the costs associated with exporting. If this were the case, we would expect the cut-off productivity level for which firms find it profitable to start exporting to be lower for connected than non-connected firms. Thus, in connected industry-county combinations, less productive firms would select into exporting, resulting in lower profitability for exporting firms. A similar effect might also exist for firms entry decisions. As we only observe private firms that have output greater than 5 million RMB, it is possible that despite a positive effect on a given firm's TFP, less productive firms are able to overcome the size threshold and thus average TFPR remains unchanged. We investigate this further in section B.5, where we analyse the effect on labour productivity for the universe of firms in Guangdong.

As a second exercise, we explore whether the effects are larger for high-tech industries, where the technological gap between American and Chinese firms is the largest, and thus knowledge flows through the network are likely to be strongest. We classify industries according to the technology intensity definition of the OECD, which is based largely on R&D spending intensity. Table B.18, shows no additional effect for high tech industries.

Overall, we find little evidence that technological knowledge flows are driving our results, though we are unable to establish whether they have an additional effect on connected firms. Instead, our results are consistent with networks reducing the profitability threshold of exporting.

**Foreign Investment**

In this section we investigate whether foreign investment has an effect on exports. As outlined in section 3.3, ethnic networks might encourage foreign direct investment (FDI). This might itself cause firms to export more, or increase knowledge transfers. In this case, we should expect the observed increase in exports to be (at least partly) explained by an increase in FDI. Although our main analysis focuses on domestically owned firms, we are also interested in understanding whether the increase in exports for other firms is driven by FDI.

We explore this question by analysing all privately owned firms while controlling for the share of total equity that comes from a foreign source. Table B.12 shows the results on both the probability of exporting in columns (1) to (3) as well as on the logarithm of the value of exports in columns (4) to (6). The share of foreign capital itself has a positive effect on both the probability of exporting and the value of exports conditional on the firm being an exporter, documenting a positive relationship between foreign ownership and exporting. However, the coefficients of all three measures of network exposure are similar in magnitude to the baseline model and highly significant, indicating that the positive effect of higher exposure to the network cannot be explained by an increase in foreign capital share.

Moreover, we regress the share of foreign capital on network exposure (figures B.3 and B.4), which is discussed in more detail in section 3.8. We can only observe a positive effect on non-exporting firms, further indicating that while networks might increase foreign direct investment, this is not the most important channel.

## 3.8 Results: Other Firm Variables

In this section, we analyse how exposure to the American Chinese network affects other firm variables in addition to exports.

Figure B.3 shows the effect of our three measures of network exposure on total output, domestic sales, profits, fixed assets, capital and the share of capital that is foreign owned. While not all measures have a significant effect, they nevertheless follow the same pattern. There is a positive effect on output of 4.9% -5.8% and an increase in profits of 4.3-5.5%. Similarly, fixed assets increase by 5.6-7.1% and total capital by 8.2-10.7%. On the other hand, domestic sales seem to decrease: both the retail and same industry networks have a large negative effect, of around 13.1 to 15.6%. The effect of the downstream manufacturing network is similar in magnitude, but the estimate displays very large standard errors. The negative effect on domestic sales, together with a positive effect on exports, provide suggestive evidence of specialization of connected firms in exportable varieties, which are less demanded in the domestic market. The effect on the share of capital that is foreign owned is not statistically significant.

Figure B.4 splits the sample into exporting and non-exporting firms and shows that most of the effects are driven by exporting firms. It is important to keep in mind that exposure to the overseas network affects selection of firms into exporting, and therefore these results cannot be interpreted as causal. Output, profits, fixed assets and total capital of connected exporting firms are higher. The decrease in domestic sales is very large: a one standard deviation increase in our measure of exposure to the network in related retail and wholesale industries reduces domestic sales by 26.1%. The fact that the effect is the largest for retail and wholesale exposure is consistent with Chinese firms specialising in goods that appeal to American consumers but are not tailored to Chinese consumers' tastes. We can also observe that the effect for non-exporting firms is close to zero or negative in terms of output and domestic sales, despite being positive (although not always statistically significant) in terms of fixed assets and total capital. This could be caused by compositional effects, as access to the network may reduce the average productivity of non-exporting firms by driving more firms to export. Finally, we also observe a positive effect on the share of foreign capital of non-exporting firms.

We further investigate how our measures of exposure affect variables regarding employment. Figure B.5 shows that while total employment is unaffected, both the share of high skilled workers as a percentage of the total workforce and management expenses are higher for connected firms; the size is around 1 percentage point for the first and up to 8% for the latter. Further, wages per worker are between 1.1 and 1.6% higher. Figure B.6 shows that the effect is again nearly exclusively driven by exporting firms. These findings are consistent with connected exporting firms specialising in products of higher quality or with more complex production processes, which require higher skilled workers. However, higher management expenses could also be explained by the fact that exporting requires a greater number of managers as operations become more complex. Non-exporting firms exhibit a very different pattern on the other hand. While most effects are not statistically significant from zero, exposure to the network in downstream manufacturing industries is associated with a decrease in employment and total wages, while exposure to the network in the same industry is associated with an increase of 1 percentage point in the share of high skilled workers. This may be suggestive of knowledge diffusion about production processes through the network, which allows firms to complete more complex operative processes and which in turn require more high skilled workers.

## 3.9 Alternative Explanations

### 3.9.1 Specific Skills of Sending Counties

One alternative explanation that could give rise to predictions consistent with our observations is one of specific skills or technology locking. The idea is that in the case of increasing returns to scale or the passing down of specific skills or human capital across generations, initial conditions can imply that areas or groups have a competitive advantage in certain industries (Arthur, 1989). In this case, one could imagine that the sending counties as well as the Cantonese areas have specialised in certain industries, in which they have a competitive advantage and therefore, they are more likely to export. At the same time, the descendants of these areas also have a competitive advantage and therefore sort into working in these industries in the U.S. As mentioned in the historical background section, the sending counties were quite underdeveloped, agrarian areas and the emigrants to the U.S., with the exception of a small number of merchants, were blue collar workers from the agricultural sector. In the U.S. these individuals first worked in the gold mining sectors and participated in the building of the railways. Later, the most important occupations were within laundries and restaurants. [SOURCE]. There is therefore little history of manufacturing either in China nor in the U.S. Our results, by contrast, are only within manufacturing. To further test this alternative explanation, we restrict our analysis to industries that have not existed historically in the sending counties. Due to the political instability of the region during the early 20th century, there exists only anecdotal evidence on the industry composition of these areas. Therefore, we restrict the analysis to high- and medium-tech industries, which are all exclusively modern industries. The results are presented in Table B.20. [5] The results remain mostly robust, though significance is lost in some cases possibly due to the reduced sample size.

[5] i.e. examples of such industries includes manufacturing of aircraft and space craft , IT machinery and cars and the pharmaceutical industry.

### 3.9.2 Relocation of Trade

The previous discussion mostly supposed that networks increase trade, by lowering marginal or fixed costs of trade. However, it is important to note that our empirical strategy only captures the relative probability of exporting of areas that were treated compared to those that are not. Therefore it could capture either that trade remained unchanged in non-treated areas and increased in the treated areas or instead that trade was relocated from non-connected areas to connected areas. In this way, we might be possibly overstating the positive effects of networks on trade or even capturing pure nepotism, which reduced exports from more efficient but less connected firms to more connected ones. Such nepotism is likely to be more important for industries, which are more connected, hence being consistent with our observations. As we have a single cross-section, it is very difficult to distinguish between these two effects. It is therefore important to keep in mind that the effects we observe may not necessarily be welfare enhancing.

## 3.10 Conclusion

In this paper, we analyse how exports of Chinese firms are affected by access to the ethnic Chinese network in the U.S. We exploit an historic migration wave that lasted from the mid-19th century until 1949. The localised nature of this migration wave, together with the linguistic heterogeneity of southern China allows us to implement a difference-in-difference strategy with continuous treatment intensity: The main explanatory variable of interest is a dummy variable which equals one if a given firm in Southern China is located in a sending county, i.e. if the firm has a higher "cultural" exposure to the network, interacted with the number of American born Cantonese employed in a related industry in the U.S., which measures the "industry exposure". For the latter, we define 'related industries' in three different ways: firstly, as the same industry, secondly, as related retail and wholesale industries and thirdly, as downstream manufacturing industries.

We find that using all three measures of industry exposure, greater access to the American-Chinese network translates in significantly higher exports, both in terms of the probability of exporting as well as in the value of exports conditional on exporting. Moreover, we find a smaller but significant effect of the interaction of industry exposure with a dummy indicating whether a firm is located in a Cantonese speaking area. The fact that we find results both for the extensive and intensive margin indicates that the effects cannot purely be driven by a reduction in fixed costs. The results remain robust to a number of specifications. Furthermore, we find evidence that the effects are driven by differentiated goods, pointing towards networks alleviating information constraints.

One of the main contributions of paper is to analyse how other firm variables are affected by higher exposure to the ethnic network. We find that total factor productivity remains unchanged, and is even reduced for non-exporting firms, possibly due to a greater mass of firms selecting into exporting. Moreover, we observe that connected firms are larger in terms of output, employment, capital and assets, employ a larger share of high-skilled workers and have higher managerial expenses. However, we also find that domestic sales decrease with higher exposure to the network, indicating overall that connected firms are more likely to specialise in product varieties aimed at the export market but that are not suitable for domestic consumption. In so far that these export varieties are of higher quality and require more complex production processes, this hypothesis could also help explain the increase in the share of high-skilled employees and management expenses.

# Chapter 4

# Product Customisation and Optimal Firm Size

## 4.1 Introduction

It has become much of a stylised fact in the development economic literature that industries in developing countries are characterised by a much larger share of small firms than developed countries (e.g. Gollin (2008)). But what exactly are the factors that cause this different distribution? Most of the previous literature has concentrated on productivity differences in explaining size differences for firms in developed countries (e.g. Melitz (2003)), and, in the developing country context, on constraints to firm growth, such as credit constraints or labour constraints (e.g. De Mel et al. (2008)) or distortions tilting the playing field inf favour of small firms (Restuccia and Rogerson, 2013). In contrast, this paper hypothesizes that the difference in firm size indicates that these firms perform vastly different functions, the profitability of which depends on transport costs and consumer incomes. More specifically, I propose that small firms tailor their goods exactly to consumers' preferences using more flexible production processes with a higher marginal cost. In contrast, large firms produce a single variety at a lower marginal cost. Furthermore, large firms are able to ship their products across locations. The transportability is key in explaining the size difference: customised firms are smaller due to higher marginal costs and due to being limited to single locations.

The fact that small firms dominate in developing countries has been well documented in the literature. Gollin (2008) for example highlights that the dominance of small firms is not only found in agriculture and the service sector: even in manufacturing, large fractions of the workforce are self-employed which often translates into small firm size. He gives as an illustrating example that in Ghana more than 75 percent of manufacturing workers are employed in firms with less than 10 workers. In contrast, in the US, like in most rich countries, small firms play a very minor role. For instance, firms with less than 20 employees make up only 5 percent of the total manufacturing workforce. This evidence fro Ghana and the US is in line with a large amount of evidence documenting a negative correlation between GDP per capita and an emphasis on small scale production across countries but also over time (Poschke, 2014), which suggests that as countries grow richer, small businesses play a less and less important role. Finally, a large share of the micro firms, i.e. firms with less than 10 workers are located in rural areas in developing countries (Ghani et al., 2014, 2012). This is in contrast to evidence from the US, where smaller firms seem to locate in urban areas (Holmes and Stevens, 2014).

Much of the previous literature has concentrated on explaining these size differences along two lines: Firstly, explanations that restrict the growth of small firms from becoming larger, such as for example credit constraints (Aghion et al., 2007) or insecure property rights (De Soto, 1990). The second group of explanations on the other hand, suppose that large firms are disadvantaged in developing countries, due to higher fixed costs. These explanations are usually based on a 'dual-economy model', which assumes that there are two types of technologies, modern and traditional, and which are associated with different sizes and different fixed costs. Due the fact that the modern technology's fixed costs are prohibitively large in developing countries, only the most productive entrepreneurs find it profitable to set up a firm and thus the share of large firms is smaller (Banerjee and Duflo, 2005). This dual economy idea is also consistent with the assertion by the McKinsey Global Institute (2001) that the most productive firms in developing countries are as productive as those in developed countries.

My model fits in the dual economy literature, as there are two alternate technologies, one mechanised and one traditional, that are associated with different marginal costs. However, I add an important aspect, namely that (manufacturing) firms of different sizes could be providing very different type of goods, as has been suggested by Holmes and Stevens (2012) for the US: While large firms produce a standardised good that can be transported to several locations, small firms produce a customised good that is harder to transport. Thus customised firms have a much smaller size than standardised firms. I use how the profitability of each technology varies with transport costs and income levels in order to explain the differences in firm size distributions across countries.

I incorporate this dual technology into a spatial competition model with heterogeneous firms. Following, Salop (1979), I assume the product space is represented by a unit circle and consumers are distributed uniformly around the circumference. Furthermore, there are a number of local markets. Each customised firm operates in one of the local markets. Standardised firms are located in a central location, and can choose to ship to each local market for a fixed costs, or exit. The only input to production is labour. Standardised firms different in their productivity, but are assumed to be always more productive than the customised firms. In the first stage of the game, standardised firms decide which markets to ship to. In the second stage, the standardised firms choose prices for each market. In the final stage, customised firms choose their prices and demand is realised. I allow firms to choose a different price for each variety-market pair. However, firms are not allowed to price discriminate in the sense of charging different prices for the same variety.

It is important to note that in this model, there may not be a pure-strategy equilibrium in the pricing stage (d'Aspremont et al., 1979), as profits may not be continuous nor convex. Thus, I make two simplifying assumptions: Firstly, I fix the location of all standardised firms at a distance from each other of $\frac{1}{n}$. Secondly, I only consider cases, where, in a given market, the customised firm sells to a positive mass of consumers between each two standardised firm i.e. to consumers whose ideal variety is located between the varieties provided by the standardised firms. This implies that each standardised is only in competition with the customised firm, which in turn allows me to abstract form the strategic interactions between different standardised firms.

The main parameters that affect the market share of customised and standardised firms are transport costs, income levels and population size. Population size increases the number of markets each standardised firm is willing to ship to, by reducing relative fixed costs. Transport costs affect the effective marginal costs of the standardised firms, and thus makes them less competitive compared to the customised firms. Thus, in a given market, standardised firms' market share is reduced and as a result the standardised firm ships to fewer markets. Thus, there is a smaller share of large firms, but also the size of large firms is decreased. Income, finally, has a non-monotonic effect as on the one hand, it increases the cost advantage of the standardised firms, but on the other hand, the taste for customisation is allowed to be an increasing function of income. Under certain parameter restrictions, the model predicts that at low levels, income decreases the share of small firms, while if income becomes high enough, the share of small firms increases again. In this way, the model is able to capture both the evidence from developing countries, where poorer areas areas are associated with smaller firms and the evidence from Holmes and Stevens (2014), who observe that in the U.S. rich and densely populated areas have the largest share of small firms.

Anecdotal evidence of this mechanism highlighted in my model can be found in the development literature.Ng'ang'a (2012) for example claims that

> *"Salient characteristics of the domestic market oriented industrialization industries (such as the woodworking industry in Kenya) include, high transport costs, which protect them from the competition of import (Oloya 1992). (...). It has been noted that the expansion in this type of industries in Kenya has been more in the increase of the number of small firms since the optimum scale of production is small (Oloya 1992)."*

Ove Pedersen (1995) gives even more specific evidence on the difference in the goods supplied by small and large firms:

*"The building material market (in rural towns in Zimbabwe) is dominated by standardized mass-produced items distributed both by local building material dealers and by non-local merchants(...). Still some small local producers manage to compete. By selling directly from the workshop they have very low distribution costs; often they also produce a lower quality and, therefore, cheaper product. However, the increasing demand has initiated a certain product specialization where the small workshop produces custom-made window frames, burglar bars or specialized building blocks, which the large enterprises do not produce."*

This quote demonstrates the core idea behind my model, namely that even though both kinds of firms might operate in the same market and within the same industry, they provide very different goods, the production of which seems to be linked to different optimal sizes. Hence, the question why there are so many small firms in developing countries is linked to the question why there are so many firms producing customised and not standardised goods.

There has been a general consensus in policy circles that bad transport infrastructure is a key impediment to growth. This holds even within countries: for example Stifel and Minten (2008) find that there is a strong spatial overlay between remote areas and impoverished areas. While this does not allow us to establish a causal relationship it does seem indicative that transport costs play an important role. The difference in transport costs across countries and its impact on firms is also the focus of Gollin and Rogerson (2014) who investigate in how far high transport costs can explain the prevalence of the subsistence sector in Uganda. They find that the transport costs are significantly higher in Uganda compared to the US (4-10 times higher per kilogramme transported). Their model predicts that the population active in the subsistence market is highly sensitive both to agricultural productivity and transportation costs. Transportation costs have also been linked to misallocation, such as by Asturias et al. (2014), who propose that high transportation costs that result from poor infrastructure generate misallocation by increasing the dispersion in market power across firms in different location.

This paper adds to the literature that identifies demand factors as a key determinant for firm size and productivity in developing countries. The two closest related papers are Lagakos (2013) and Kothari (2014). Lagakos (2013) aims to explain the large productivity difference in the retail sectors between high and low income countries through the adoption of two different technologies - a low productivity and low fixed cost retail technology (e.g. a corner store) or high productivity and high fixed costs technology (e.g. large retailer). As in this paper, the profitability of either technology is determined by demand factors that depend on market size and transport costs. However, there are significant differences between this paper and Lagakos (2013), which stem in part from the fact that I analyse the manufacturing and not the retail sector. In Lagakos (2013) only the consumers' (transport) costs are affected by the technology used, in this paper both consumers and firms pay a cost (customisation and shipment costs respectively). Thus this model combines demand with supply factors, in explaining the choice of technology. Kothari (2014), on the other hand argues that poorer states in India are characterised by smaller firms because they have high demand for low quality products, which incur a lower fixed cost and thus can be produced efficiently in small plants. They find that their model can explain a significant portion of the cross-country variation. However, there is no link between transport costs established.

Another related paper is by Holmes and Stevens (2014), who also try to explain the differences in sizes in the manufacturing sector by a choice of product or technology, albeit using a very different methodology. Similarly to this paper, their technology choice lies between providing a specialised/customised good or a standardised good. However, they arrive at very different predictions by the model, namely that customised goods are only produced in large and richer markets. In the developing country context this would imply that the small markets in rural areas would be supplied exclusively by standardised goods and thus be characterised by few large firms, which does not seem to match the data.

Furthermore, this model links to the literature that claims that agglomeration/ urbanisation can lead to growth through structural transformation (Venables 2010, World Bank 2009, Overman and Venables, Henderson 2010) and to Gollin et al. (2013), who link urbanisation with the presence of production of more or less tradable goods, specifically the link between urbanisation and the structural transformation towards a larger manufacturing sector.

Finally, methodologically the model presented in this paper is close to the spatial competition models following the seminal contributions of Hotelling (1929) and Salop (1979). However, as I allow for heterogeneous productivity, the model is closest to Vogel (2008), who establishes an equilibrium with spatial competition, though I undertake important simplifications to make the model more tractable.

The rest of the paper proceeds as follows: Section 4.2 up to section 4.4 lay out the model and the equilibrium. Section 4.5 discusses comparative statics, while section 4.5.2 discusses empirical predictions. Section 4.5.2 concludes.

## 4.2 Setup

There is a central location $Z$ and $M$ local markets. Each local market is indexed by $m = 1, 2, ...M$ and is located at a distance $d_m \in [0, d_{max}]$ from the central location. There are no consumers located at the central location. In contrast, each local market is characterised by a mass of consumers $L$ with wage w. The product space is represented by a circle with unit circumference. There is a continuum of locations on the circle, each representing a product variety.

Suppose producers can be of either of two types: standardised or customised $t \in s, c$. A customised producer can produce all possible product varieties but can only locate in and sell to one local market. There are $N^{s*}$ standardised producers. A standardised firm can produce one single variety in the product space. It is located in the central location but can ship to any local market by incurring the transport cost $td_m$. As such, define the number of producers of either type that are selling in each market as $N^t_m$. I assume that there is one customised firm active in each local market. There are four periods. There $N^s$ standardised entrants, which upon entry, draw their cost parameter, after which they decide to either exit or, it they produce, to which markets to ship. In the following, second, period standardised firms then choose their prices. In the final period, customised producers set their prices and demand is realised.

### 4.2.1 Consumers

Each local market has a mass of $L$ consumers with wage $w$. I assume that wages are constant across markets. Each consumer $l$ has a preferred variety, which is represented by their location on the circumference of the circle that represents the product space. Consumers are assumed to be distributed uniformly around this circle. Each consumer inelastically demands one unit of the good if the location-adjusted price is less than their reservation value $v_m$. I assume throughout that reservation values are sufficiently high such that all consumers in a given market purchases a good in equilibrium even if there is only a customised firm operating in the market. A given consumer with ideal variety $l$ in local market $m$ with a finite set of producers $N_m^t$ purchases one good from firm $i \in N_m^t$ if

$$i = \arg\min_{j \in N_m} \ p_{j,m} + \theta|l - j| \ \text{ and } \ p_i + \theta|l - i| \leq v_m \tag{4.1}$$

where $|l - j|$ is the shortest arc-length separating firm j from consumer z. The parameter $\theta > 0$ is the cost per unit of distance in the product space incurred by the consumer, implying that $\theta|l - j|$ is the cost the consumer incurs from consuming a variety of distance $|l - j|$ from their ideal variety $l$. Further, I assume that $\theta = h(w) = w^{\beta}$ i.e. the cost from consuming a variety different from the ideal variety is increasing in wages. Furthermore, assume the following tie breaking rule:

**Assumption 1** *If the above equation holds with equality, i.e. the adjusted prices offered by both firms are equal, then the consumer will purchase from the firm that provides the variety closest to his/her preferred variety. If any two or more firms offer the same adjusted price for the same varieties, the consumer randomises over the firms.* [1]

[1] The predictions of the model remain unchanged if a different tie breaking rule is assumed.

### 4.2.2 Producers

There are two types of producers: Standardised firms and customised firms. Labour is the only input in production. Each standardised firm $i \in N^s$ can only produce one variety $a_i$ produced according to the production function $y_{s,i} = A_i^s w^\alpha$, where $A_i^s$ is the firm specific productivity and $w$ is the wage. Thus each firm is characterised by a marginal costs $k_i = \frac{w^\alpha}{A_i^s}$. Here, I make the following assumption:

**Assumption 2** *Assume that $2\alpha < \beta$ i.e. that the taste for customisation $\theta$ increases more with wages than the marginal cost $k_i$.*

In addition to marginal costs $k_i$, standardised firms incur a transportation cost of shipping one unit to a given market $m$ of $t \cdot d_m$. Thus, the cost of producing a good to be consumed in market m at distance $d_m$ from the central location is given by:

$$k_i + t \cdot d_m$$

Finally, standardised firms have to pay a fixed cost for each local market they are shipping to of $f_s$, which could be seen for example as the cost of establishing a supply chain.

At the beginning of the first stage, there are $N^s$ standardised firms [2], which draw their productivity parameter $A_i^s$ from a common distribution $g(A_i^s)$. $g(A_i^s)$ has positive support over $(A_{min}^s, A_{max}^s)$, where $A_{max}^s < A^c$ and has a continuous cumulative distribution $G(A_i^s)$. The productivity level $A_i^s$ translate into the marginal cost of $k_i = \frac{w^\alpha}{A_i^s}$. After receiving a low productivity draw, a firm may decide to immediately exit and not produce. If the firm decides to remain and produce, it is allocated a variety $a_i$. For simplicity, I assume that all firms' varieties are located at an equal distance across the product space i.e. the distance between firm i and its neighbour $i+1$ is given by $|a_i - a_{i+1}| = \frac{1}{N^s}$ [3]. In the

[2]I am not able to model entry fully as due to assumptions made later in this section, profits are independent of the number of standardised firms.

[3]In this way, I follow Salop (1979). On the other hand, Vogel (2008) proves that if we allow firms to choose their location, more productive firms actually choose more isolated locations. For the purpose of this paper however, the exact location plays only a minor role. In fact, I can show that given that the parameter restrictions I impose hold, standardised firms are indifferent to their location (It affects only the profits of the customised firm).

same stage, each firm chooses which markets to supply to, $M_i$ and pay marginal transport cost $td_m$ as well as the fixed cost $f)_s$. Standardised firms then choose their prices in the third stage. I assume that firms are not able to price discriminate across consumers within the same market, i.e. are restricted to charging the same price for a given variety to all consumers. However, they are able to price-discriminate across locations and charge different prices for each local market. Thus, they are able to choose as many prices prices as local markets they are selling to. Let $\varphi^s_m(a,p)$ be the set of locations at which consumers in market $m$ buy from firm i. In this case, profits of the standardised firm are given by:

$$\Pi_i = \sum_{m_i=1}^{M_i^*} \varphi(p_i)\big(p_i - k_i - td_m\big) - f_s \tag{4.2}$$

On the other hand, each customised firm $j$ can produce all possible varieties $a_{j,m} \in [0,1]$. As for standardised firms, I assume that each firm is only able to charge one price for each variety produced. Thus, the customised firm is able to choose a set of prices $p_{j,m}(a_{j,m}) \in [0,\infty)$ and $a_{j,m} \in [0,1]$ . In turn, customised firms are less efficient at producing i.e. are characterised by the production function $y = A^c w^a lpha$, where $A^c < A^s_{max}$. Thus, each customised firm is characterised by a cost parameter parameter $\kappa = \frac{w^\alpha}{A^c}$. Furthermore, I assume that the customised good is not transportable, i.e. needs to be supplied by a firm in the same local market as the consumers are located in. This assumption is motivated by the fact that in producing a customised good requires the movement of people and not just goods, which incurs a much higher transport cost. [4].The customised firm sets its prices in the final and third stage of the game, after observing the behaviour of the standardised firms.

It is important to note, however, that abstracting momentarily from the customised technology, solving for the standardised firm's optimal price is not straightforward. d'Aspremont et al. (1979) have shown that if locations are endogenous and are decided before prices are set, there is no subgame perfect equilibrium if firms are located "too closely".

[4]This is not a crucial assumption; as long as transport costs for the customised good are sufficiently higher than for the customised good, the results follow through.

This is caused by the fact that firms profits are non-convex and non-continuous. The problem is exacerbate when firms are heterogeneous in terms of productivity as is the case here. There have been a number of solutions proposed to this problem: from convex transportation costs (d'Aspremont et al., 1979) to allowing firms to randomise over prices (Vogel, 2008). As modelling the strategic interactions between standardised firms is not the focus of the paper, I choose the easiest abstractions and fix locations and limit differences in productivity such that a subgame perfect equilibrium exists. This is the case where no standardised firm is *undercut* by another standardised firm in each market it chooses to ship to i.e. each standardised firm supplies to a positive mass of consumers.

**Assumption 3** *Assume conditional on shipping to particular market, that no standardised firm is undercut by another standardised firm for price vector* $p^s$*. A firm is undercut if it supplies to no customers in a given market.*

Furthermore, I simplify the analysis further by making the following assumption:

**Assumption 4** *Assume that the customised firm is not locally undercut for any standardised neighbours i and i+1. A customised firm c is locally undercut if it makes no sales in the set of of consumers* $L_{i,i+1} \in [a_i, a_{i+1}]$ *for all standardised firms* $i = \{1, ...n\}$.

While this is undoubtedly a strong simplifying assumption, the main implication for the model is that it allows us to ignore the strategic interactions between the standardised firms, which are not the focus of this paper. These considerations would not be straightforward, as profits would become non-continuous and non-convex, as mentioned previously. I will later show, under which parameter restrictions these assumptions hold along the equilibrium path.

As discussed previously, the game unfolds in three stages. In the first stage, standardised firms draw their productivity and decide to exit or, if they remain active, to which markets to ship. In the second stage, the price stage, all firms observe number of competitors by type and their location. Standardised firms then simultaneously choose their prices for each market , $p_{im} \in [0, \infty)$. A pure strategy in this stage is a mapping from a location-market pair, **(l,m)**, into prices. Finally, in the third stage, customised firms choose their prices $p_{j,m}(a_{j,m}) \in [0,\infty)$. A pure strategy in this stage is a mapping from a location, **(l)**, into prices.

## 4.3 Within-Market Equilibrium

The solution concept is a Subgame Perfect Nash Equilibrium and proceeds from the following proposition:

**Proposition 1** *For any set of parameters $(t, \theta, L, N^s, \kappa)$ there exists is a non-empty set $O* \in \Omega^n$ such that $\omega \in O*$ is an SPNE. The set $O*$ has there following properties:*

1. *Strategies are pure.*
2. *For any order of the firms around the circle there exits a corresponding $\omega \in O*$.*
3. *If no standardised firm ships to market m, firm c's prices, market share and profits in market m are given by:*

$$p_c(l) = v_m$$
$$x_{c,m} = 1$$
$$\Pi_{c,m} = v_m - \kappa$$

4. *If at least one standardised firm ships to market m, firm c's prices, market share and profits in market m are given by:*

$$p_{c,m} = max\left\{min\left\{\tfrac{1}{2}(k_i + td_m + \kappa) + \theta|l - a_i|, \tfrac{1}{2}(k_i + td_m + \kappa) + \theta|a_{i+1} - l|\right\}, \kappa\right\} \forall i, i+1 \in N^s$$

$$x_{c,m} = max\left\{1 - \frac{N_m^s}{\theta}\left(\kappa - \bar{k}_m + td_m\right), 1\right\}$$

$$\Pi_{c,m} = \sum_{i=1}^{N^s} \frac{1}{2\theta}\left[\frac{k_i + k_{i+1}}{2} + td_m + \theta\frac{1}{N_m^s} - \kappa\right]^2$$

5. *Firm $i \in N_m^s$'s price, market share and profits in market m are given by:*

$$p_{i,m} = k_i + \frac{1}{2}(td_m + \kappa - k_i)$$

$$x_{i,m} = \frac{\kappa - k_i - td_m}{\theta}$$

$$\Pi_{i,m} = \begin{cases} \frac{1}{2\theta}\left[\kappa - k_i - td_m\right]^2 & \textit{if } d_m \geq \frac{\kappa - k_i}{t} \\ 0 & \textit{otherwise} \end{cases}$$

As can be seen in point (3), if there is no standardised firm active in market m, by assumption the customised firm serves all consumers and hence its market share is equal to one. As it can perfectly price discriminate, it charges each consumer his or her reservation price. If however, at least one standardised firm operates in market m, prices, market shares and profits of the customised firm are given by the equations in point (4). The market share of the customised firm in this case depends on the average cost advantage of the standardised firms, i.e. $\kappa - \bar{k}_m - td_m$ and the number of standardised firms. The cost advantage of the standardised firms depends in turn on their average marginal costs as well as on the transport costs. It can easily be seen that in markets that are at a higher distance from the central location i.e. have a higher $d_m$ and if transport costs are higher , the customised firm will have a higher market share. Finally, the market share of the customised firm also positively depends on $\theta$ i.e. the taste for customisation of the consumer. Again, the customised firm can perfectly price discriminate i.e. it will set prices such that the consumer is indifferent between consuming form it or the standardised firms, as long as prices are above its marginal cost. Thus, for each consumer it will charge the maximum of either its marginal cost or the price of the closest standardised firm plus the utility the consumer would lose by consuming the standardised good instead of its ideal variety. The market share, prices and profits of the standardised firm in any market it decides to be active in is given by point (5) of the equilibrium proposition. Prices are given by the marginal cost plus a mark -up, which is equal to half of the difference in marginal costs between the customised and standardised firm. The market share of the standardised firm, clearly mirrors that of the customised firm: i.e.

it depends positively on the cost advantage over the customised firm, as I previously limited myself to the cases where the customised firm is the relevant competitor. If the cost advantage of the customised firm is large, even consumers whose ideal variety is relatively distant to that of the standardised firm will purchase the latter product. If however, the cost advantage is relatively low, then only consumers whose ideal variety is close to the one produced by the standardised firm will purchase from it, even though the standardised firm remains cheaper. In addition, how many consumers purchase from the standardised firm depends on the taste of customisation of the consumers. The higher $\theta$, the less the price advantage of the standardised firm can compensate consumers for the decreased utility received from consuming the standardised product instead of their ideal variety. A formal proof of the proposition can be found in the appendix.

## 4.4 Stage 1: Shipping Decision

Recall, that there are $N^s$ standardised firms in the central location. At the beginning of the first stage, each standardised firm draws their productivity level $A_i$ from a common distribution $g(A)$ with a support over $(A_{min}, A_{max})$, which translate into the firm-specific cost parameter $k_i = \frac{w^a lpha}{A_i}$ After drawing their cost parameter, each entrepreneur decides the markets, $M_i^*$, to which they want to ship to, or exits. I assume firms exit when they do not find it profitable to ship to a market at zero distance from the central location. If a standardised firm decides to ship to a local market it incurs a fixed cost $f_s$ for each market. This can be thought of as the cost of establishing a supply chain. Total profits across all markets for firm i are given by:

$$\Pi_i = \sum_{m=1}^{M_i^*} \Pi_{i,m} - f_s \tag{4.3}$$

where $\Pi_{i,m}$ are the profits earned in each local market, where local profits are given by equation C.13. It is clearly optimal for firm i to ship to all markets where marginal profits are greater than zero i.e. $\Pi_{i,m} - f_s > 0$. Thus, there standardised firm i ship to all markets that are at a distance $d_m$ such that:

$$d_m \geq \frac{1}{t}\left(\kappa - k_i - \frac{\sqrt{2\theta f_s}}{L}\right) \tag{4.4}$$

This implies that that the higher the transport costs, the smaller the expected market size in terms of consumers ($L$) and the higher the taste for customisation ($\theta$), the smaller the distance the standardised firm is willing to ship. Furthermore, more productive firms (with a lower $k_i$) ship to markets that are located further from the central location. Thus more productive firms are not only larger due to having a higher market share within each market, but also as they ship to a larger number of markets.

Suppose there exists an equilibrium where a positive mass of firms exit, while a positive mass of firms choose to ship to at least one market. This implies, that an entrant remains active if and only if its productivity parameter $A_i$ is sufficiently high. Therefore, there exists a cutoff marginal cost, $A^* \in (A_{min}, A_{max})$ such that for any $A_i < A^*$ the firm decides to sell to no market. This implies that its profit $\Pi_{i,m}$ of a market at the closest distance net of the fixed cost $f_s$ is equal to zero. This is the strongest, when the distance is equal to zero. This cut-off level of marginal costs is given by:

$$A^{s*} = \frac{w}{\kappa - \frac{\sqrt{2\theta f_s}}{L}} \tag{4.5}$$

Similarly, we can find a cutoff marginal costs for each local market such that any firm with a marginal cost higher than $A_m^{s*}$ will not ship to market $m$, and which is given by:

$$A_m^{s*} = \frac{w}{\kappa - td_m - \frac{\sqrt{2\theta f_s}}{L}} \tag{4.6}$$

The exact number of firms active in each market is stochastic. However, the expected number of firms that will be active in market $m$, is given by:

$$E(N_m^s) = N^s \cdot P(A_i^s \geq A_m^{s*})$$

These conditions are summarised in the following proposition:

**Proposition 2** *Any standardised firm i will exit if its productivity is below the cutoff productivity level:*

$$A^{s*} = \frac{w}{\kappa - \frac{\sqrt{2\theta f_s}}{L}}$$

*Conditional on remaining active, standardised firm i ships to all markets, which are at a distance $d_m$ from the central location such that:*

$$d_m \geq \frac{1}{t}\left(\kappa - k_i - \frac{\sqrt{2\theta f_s}}{L}\right)$$

*And the expected number standardised firm shipping to each local market is given by:*

$$E(N_m^s) = N^s \cdot P\left(A_i^s \geq \frac{w}{\kappa - td_m - \frac{\sqrt{2\theta f_s}}{L}}\right)$$

## 4.5 Comparative Statics

In this section, I analyse the key parameters of the model affect the market share of customised firms (as given by equation C.15) and the number of standardised firms selling to a given market (as given by equation 4.4). This allows me to infer the effect on the average size of standardised firms. The variables of interest are specifically transport costs ($t$), population ($L$) and wages ($w$). In this section, for simplicity, I assume that $A_i$ is distributed uniformly $U \sim [A_{min}, A_{max}]$. In this case, the expected number of firms is given by equation 4.4. Average marginal costs of standardised firms in market m is then given by:

$$\bar{k}_m = \frac{1}{2}\left[\kappa - td_m - \frac{\sqrt{2\theta f_s}}{L} - \frac{w}{A_{min}}\right] \tag{4.7}$$

and the expected number of firms is given by:

$$E(N_m^s) = N^s \cdot \left(A_{max}^s - \frac{w}{\kappa - td_m - \frac{\sqrt{2\theta f_s}}{L}}\right) \cdot \frac{1}{A_{max} - A_{min}} \tag{4.8}$$

**Transport Costs** $t$

Transport costs affect the market share of customised firm c in market $m$ the following way:

$$\frac{\delta x_{c,m}}{\delta t} = -\frac{\delta E(N_m^S)}{\delta t}\frac{1}{\theta} \cdot (\kappa - \bar{k}_i - td_m) + \frac{E(N_m^s)}{\theta} d_m + \frac{E(N_m^s)}{\theta}\frac{\delta \bar{k}_m}{\delta t} \tag{4.9}$$

Equation 4.9 shows that transport costs increase the market share of customised firms (and thus decreases the share of standardised firms) in two ways: Firstly, it makes the standardised firms less competitive compared to the customised firms, thus increasing the share of production undertaken by customised firms within a given market for a given number of active firms. Secondly, it decreases the number of standardised firms that find it profitable to ship to a given market, as increased transport costs increase the cutoff productivity level $A_m^{*s}$, which in turn decreases the expected number of standardised firms with a productivity level as well as $A_i > A_m^{*s}$:

$$\frac{\delta A_m^*}{\delta t} = d_m \cdot \frac{w}{(\kappa - td_m - \frac{\sqrt{2\theta f_s}}{L})^2} > 0 \tag{4.10}$$

However the increase in the cutoff productivity also has a negative effect on customised firm c's market share through the improved productivity of the operating standardised firms, implying that the average marginal cost of a market decreases i.e. $\frac{\delta \bar{k}_m}{\delta t}$. However, assuming a uniform distribution, it is easy to show that the first two effects dominate and this can be simplified to:

$$\frac{\delta x_{c,m}}{\delta t} = -\underbrace{\frac{\delta E(N_m^S)}{\delta t}\frac{1}{\theta}}_{<0} \cdot \underbrace{(\kappa - \bar{k}_i - td_m)}_{>0} + \underbrace{\frac{E(N_m^s)}{\theta}\frac{d_m}{2}}_{>0} \tag{4.11}$$

Thus areas with higher transport costs should have a higher share of their production taking place in customised firms and thus should have a higher share of small firms.

**Population** $L$

Population on the other hand has a positive effect on the market shares of either type, predominantly though the selection of firms that ship to a given market: if population size of each market increases, the productivity level required such that profits earned in each market cover the fixed costs is decreased, which in turn decreases the cutoff productivity:

$$\frac{\delta A_m^*}{\delta t} = -\frac{w}{(\kappa - t^2 d_m - \frac{\sqrt{2\theta f_s}}{L})^2} \cdot \frac{\sqrt{2\theta f_s}}{L^2} < 0 \tag{4.12}$$

This, however, as in the case where transport costs changed, affects the average productivity of the standardised firms that do ship to a given market, only in this case in the opposite direction. As less productive firms find it profitable to operate in a market, the average marginal cost will increase. The overall effect is characterised by the following expression

$$\frac{\delta x_{c,m}}{\delta L} = -\underbrace{\frac{\delta E(N_m^S)}{\delta L}\frac{1}{\theta}}_{>0} \cdot \underbrace{(\kappa - \bar{k}_m - td_m)}_{>0} + \underbrace{\frac{E(N_m^s)}{\theta}\frac{\delta \bar{k}_m}{\delta t}}_{>0} \tag{4.13}$$

where the first term captures the negative effect through the increased number of standardised firms that operate in a market, and the second effect captures the positive effect due to the increased marginal costs. In the case, where $A_i$ follows a uniform distribution, this simplifies to:

$$\frac{\delta x_{c,m}}{\delta L} = -\frac{E(N_m^s)}{\theta}\frac{\sqrt{2\theta f_s}}{L^2}\frac{\kappa - \frac{1}{2}\bar{k}_m - td_m}{\frac{w}{A_m^*} - \frac{w}{A_{max}}} < 0 \tag{4.14}$$

where clearly the competitional effect dominates the productivity effect.

**Wages** $w$

Finally, we analyse what happens when income increases, in our case captured by wages. On the one hand, wages increase the relative cost-advantage of standardised firms vis-a-vis customised firm, as the productivity is assumed to be labour augmenting. On the other hand, the wage or income is also assumed to increase the consumers' taste for customisation.

Due to these opposing effects, the impact of increases of wages on the market share of customised firms is more complex. Therefore, I instead analyse the effect on the market share of give standardised firm i, which is independent of the number of standardised firms (given the restrictions I imposed). Recall that the market share of the standardised firm is given by:

$$x_{i,m} = \frac{\frac{w^{\alpha}}{A^c} - \frac{w^{\alpha}}{A_i^s} - td_m}{\theta w^{\beta}}$$

Thus the market share of the standardised firm changes with wages in the following way:

$$\frac{\delta x_{c,m}}{\delta w} = \frac{\alpha\left(w^{\alpha-1}\theta w^{\beta} - \theta\beta w^{\beta}\right)\left(\frac{1}{A^c} - \frac{1}{A_i^s}\right) - \beta w^{\beta-1} td_m}{\left(\theta w^{\beta}\right)^2}$$

As I assumed that $2\alpha < \beta$, there exists a cutoff wage $w_x^*$ such that for $w < w_x^*$ $x_{i,m}$ is increasing in $w$, while for $w > w_x^*$, $x_{i,m}$ is decreasing in $w$. $w_x^*$ is given by:

$$w_x^* = \left[\frac{\beta td_m}{(\beta-\alpha)\left(\frac{1}{A^c} - \frac{1}{A_i^s}\right)}\right]^{\frac{1}{\alpha}} \tag{4.15}$$

Similarly for profits, we can find a cutoff wage $w_\pi^*$, such that below this cutoff wage, profits are increasing in wages, and then are decreasing. $w_\pi^*$ is thus given by:

$$w_\pi^* = \left[\frac{\beta td_m}{(\beta-2\alpha)\left(\frac{1}{A^c} - \frac{1}{A_i^s}\right)}\right]^{\frac{1}{\alpha}} \tag{4.16}$$

Thus, for $w < w_\pi^*$, profits are increasing in wages, and thus the cutoff productivity level for each market is decreasing in wages. This implies, that the number of firms $E(N_m^s)$ is increasing. However, when wages continue rising such that $w > w_\pi^*$, then profits of the standardised firm are decreasing in wages, and thus the cutoff profitability for each market is increasing. As such, the number of standardised firms in each market is decreasing.

### 4.5.1 Discussion

One of the main reasons why the firm size distribution has attracted such attention in development economics, is that it is associated with misallocation, which in turn is seen to be a main driver of lower aggregate TFP (Hsieh and Klenow, 2007; Restuccia and Rogerson, 2013). Thus, it is interesting whether this is supported by my model. Average market productivity is given by:

$$\bar{A} = \int_{A^*}^{A_{max}} A_i \sum_{m=1}^{M_i^*} x_{i,m} \, d_i + \sum_{m=1}^{M} x_{c,m} A_c \tag{4.17}$$

As, by assumption $A_c < A_{min}$, a higher market share of customised firms is associated with lower aggregate productivity. Thus, as long as wages are below $w*_{\pi}$, poorer markets are characterised by a larger market share for customised firms. As incomes increase, productivity is affected through two channels: On the one hand, increases in income reduce the market share of the customised firms, and thus increase productivity; but on the other hand, increases in income decrease the cutoff productivity level, which in turn decreases aggregate productivity. It is important to note that this is a partial equilibrium model, and thus the channel at play here goes in the opposite direction: it is not the dominance of small firms that leads to lower income, but instead lower incomes are causing the smaller firms' technology to be relatively more profitable and thus aggregate productivity is lower. More importantly, however, in my model lower measured, or mechanical, productivity does not necessarily translate into lower consumer welfare. As the customised firm sets its prices in a way such that all consumers that purchase the customised good are indifferent between buying from it or from the standardised firm with the lowest adjusted price. Thus, if small firms are replaced by larger firms, which seems to increase consumer welfare through lowering prices, consumers are in fact left indifferent.

### 4.5.2 Conclusion

In this paper, I provide an alternative hypothesis for the dominance of small and micro-enterprises in developing countries: I propose that small and large firms not only use different technologies, as is proposed by the dual-economy literature, but also differ in the type of good they provide. Small firms produce using a more flexible production technology, which allows them to tailor or customise their goods to each consumer. On the other hand, large firms use a more standardised technology, that limits them to producing a single variety at a lower marginal cost. The relationship between technology and size not only comes from the higher marginal cost of the customised technology but also form that fact that in contrast to customised firms, standardised firms are able to ship their goods across locations.

I build a spatial competition model with heterogeneous productivity, in which firms can be of two types, representing the two technologies. I show that markets with higher transport costs and lower population are characterised by fewer standardised and thus fewer large firms. Conditional on entry, standardised firms are smaller and serve also a smaller share of the market, despite the inherent productivity distribution remaining unchanged. Increases in income on the other hand have a non-monotonic effect: Income affects firms in two ways, as I allow income to affect not only the marginal cost differential between customised and standardised firms but also the taste for customisation of the consumer. Thus, while for low income levels increases in income increase the share of goods that are being produced using the standardised technology, after a certain threshold, the customised technology becomes profitable again and the market share increases again.

An important implication of my model is that while measured productivity is indeed lower in small firms than in large firms, this does not imply necessarily that consumers are better off when the market is dominated by standardised firms. This implies that differences in measured productivity do not necessarily translate into differences in welfare.

# Appendix A

# Farmer Bargaining Power & Relational Contracts

## A.1 Tables

| Timeline | |
|---|---|
| 1895 | Taiwan becomes Japanese Colony |
| 1900 | First modern mill founded |
| 1905 | **Sugar Industry Incentive Regulations passed** |
| 1918 | First Rice Riots in Japan |
| 1925 | **Ponlai Rice introduced in Taiwan** |
| 1931 | Second Rice Riots in Japan & **Second Rice Act passed** and Conquest of Manchuria |
| 1937 | Outbreak of Second Sino-Japanese War |
| 1939 | Outbreak to World War II |
| 1945 | Japanese Capitulation & Taiwan returned to China |

Table A.1: Timeline

| Year | Average price/ ton (in Baht) |
|---|---|
| 1927 | 116.9 |
| 1928 | 118.3 |
| 1929 | 122.9 |
| 1930 | 100.3 |
| 1931 | 58.1 |
| 1932 | 56.3 |
| 1933 | 48.8 |
| 1934 | 60.5 |
| 1935 | 61.6 |
| 1936 | 68.3 |
| 1937 | 62.7 |
| 1938 | 59.9 |

Table A.2: Thailand Prices of Rice on World Market

| Company | Name | Paddy Fields | Year Start | Sample? | Company (1928) | Name | Paddy Fields | Year Start | Sample? |
|---|---|---|---|---|---|---|---|---|---|
| 臺灣製糖會社 | Qiaozaiwan 1st | .223 | 1902 | YES | 鹽水港製糖會社 | Xinyin | .123 | 1909 | YES |
| | Qiaozaiwan 2nd | .223 | 1908 | YES | | Annei 1st | .068 | 1905 | YES |
| | Houbilin* | ? | 1909 | No | | Annei 2nd | .068 | 1912 | YES |
| | Agou | .403 | 1909 | YES | | Qiwei | .571 | 1911 | YES |
| | Donggang | .094 | 1921 | NO | | Shou | .374 | 1914 | YES |
| | Cheluqian | .998 | 1911 | YES | | Dahe | . | 1922 | NO |
| | Wanli | .298 | ? | NO | 林本源製糖會社 | Xizhou | .532 | 1909 | YES |
| | Sankandian | .180 | 1909 | YES | 新高製糖會社 | Zhanghua 1st | .884 | 1911 | YES |
| | Pulishe | .800 | 1912 | YES | | zhanghua 2nd | .862 | 1911 | YES |
| | Hengchun | . | 1927 | NO | | jiayi | .640 | ? | NO |
| | Taibei | .783 | 1912 | YES | | taizhong 1st | .849 | 1912 | YES |
| 新興製糖會社 | Xinyushanziding | .067 | 1905 | YES | | taizhong 2nd | .849 | 1914 | YES |
| 明治製糖會社 | Zongye | .115 | 1912 | YES | | tanzaiqian | ? | ? | NO |
| | Xiaolong | .003 | 1909 | YES | | zhonggang | .767 | ? | NO |
| | Suantou | .184 | 1911 | YES | | xinzhu | .767 | 1915 | YES |
| | Nantou | .460 | 1912 | YES | 臺南製糖會社 | yilan 1st | .734 | 1917 | YES |
| | Xihu | . | 1935 | NO | | yilan 2nd | .734 | 1920 | NO |
| 大日本製糖會社 | Taiwan 1st | .236 | ? | NO | | yujing | .262 | 1913 | YES |
| | Taiwan 2nd | .236 | ? | NO | 臺東製糖會社 | Binan | .218 | 1916 | YES |
| | Douliu | .499 | 1912 | YES | 帝國製糖會社 | Tanzi | . | 1918 | NO |
| | Huwei 1st | . | 1909 | YES | 帝國製糖會社 | Zhunan | . | 1913 | NO |
| | Huwei 2nd | . | 1912 | YES | 新竹苗栗會社 | miaoli | . | 1920 | NO |
| 東洋製糖會社 | Nanjing | .634 | 1909 | YES | 沙轆 | shalu | . | 1922 | NO |
| | Wushulin | .665 | 1911 | YES | 三五 | Yuancheng | . | 1934 | NO |
| | Douliu | .499 | 1912 | YES | | | | | |
| | Beigang | .00 | 1912 | YES | | | | | |
| | Yuemei | .683 | 1914 | YES | | | | | |
| | Wuri | . | 1922 | NO | | | | | |

Table A.3: List of Mills

The sample is restricted to mills having been founded before 1918 but which are still active in 1930.*Houbilin is excluded from the sample when the share of paddy field is used as measure of rice suitability, as it is the only mill for which I cannot distinguish between rain-fed paddy fields and dry fields.

| | Total Lending & Inputs (log) | | | Monetary Loans (log) | | Inputs Provided (log) | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| post* paddy | -.196*** | -.142* | - .105 | -.286*** | -.209 | -.066 | -.036 |
| | (.073) | (.083) | (.093) | (.134) | (.131) | (.076) | (.096) |
| post | .338*** | | | | | | |
| | (.100) | | | | | | |
| paddy | .169 | | | | | | |
| | (.341) | | | | | | |
| Factory FE | N | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y | Y | Y |
| prefecture Trends | N | Y | Y | Y | Y | Y | Y |
| prefecture Controls | N | N | Y | N | Y | N | Y |
| Mill Controls | N | N | Y | N | Y | N | Y |
| N Mills | 39 | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 360 | 331 | 360 | 291 | 360 | 291 |
| $R^2$ | .029 | .892 | .825 | .820 | .827 | .897 | .900 |

Table A.4: Loans Issued and Inputs Provided - Logged Total

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | Total Lending & Inputs ¥/hectare | | Monetary Loans ¥/hectare | | Inputs Provided ¥/hectare | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -18.596** | -18.595 | -14.936** | -21.051** | 2.828 | 2.599 |
| | ( 8.055) | ( 11.391 ) | (5.978) | (9.086) | (3.295) | (5.482) |
| post | 18.609 | 18.610 | 9.716 | 20.973 | -3.173 | -2.394 |
| | (13.016) | (18.408) | (10.385) | 14.274 | ( 5.0575) | (7.702) |
| paddy | 153.097*** | | 108.454*** | | 33.790*** | |
| | (49.355) | | (38.558) | | (12.082) | |
| Factory FE | N | Y | N | Y | N | Y |
| N Mills | 38 | 38 | 38 | 38 | 38 | 38 |
| N Observations | 76 | 76 | 76 | 76 | 76 | 76 |
| $R^2$ | .180 | .945 | .157 | .939 | .164 | .864 |

Table A.5: Loans and Inputs Provided - Pre and Post Comparison

**Notes:** Years are collapsed to a one pre-1931 and one post-1931 time periods. The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. All standard errors are robust. ***p>0.001 **p>0.05 *p>0.10

| | Monetary Loans | | | | Inputs Provided | | | |
|---|---|---|---|---|---|---|---|---|
| | Working Capital ¥/hectare | | Miscellaneous ¥/hectare | | Fertilizer ¥/hectare | | Seeds ¥/hectare | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| post* paddy | -21.168*** | -20.786*** | -4.425 | -6.043* | 2.556 | 2.163 | -1.367 | .545 |
| | (8.173 ) | (7.155) | (3.231) | ( 3.591) | (3.496) | ( 3.660) | ( 2.051) | (2.471) |
| Factory FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | Y | N | Y | N | Y | N | Y |
| Mill Controls | N | Y | N | Y | N | Y | N | Y |
| N Mills | 38 | 33 | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 291 | 360 | 291 | 360 | 291 | 360 | 291 |
| $R^2$ | .487 | .809 | .529 | .487 | .796 | .722 | .766 | .745 |
| Mean | 90.31 | 90.311 | 10.34 | 10.34 | 96.00 | 13.88 | 13.88 | |

Table A.6: Loans Issued and Inputs Provided by Type

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | Total Lending & Inputs (log) | | | Monetary Loans (log) | | Inputs Provided (log) | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| price* paddy | -36.131*** | -7.498 | -3.381 | -15.611** | -12.351** | 8.228** | 9.306*** |
| | (7.793) | (9.111) | (7.678) | (6.370) | (5.718) | (3.876) | ( 3.520) |
| price | 7.609 | | | | | | |
| | (.853) | | | | | | |
| paddy | 206.898*** | | | | | | |
| | (46.334) | | | | | | |
| Factory FE | N | Y | Y | Y | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | N | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | N | Y | N | Y | N | Y |
| Mill Controls | N | N | Y | N | Y | N | Y |
| N Mills | 39 | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 360 | 331 | 360 | 291 | 360 | 291 |
| $R^2$ | .175 | .847 | .845 | .827 | .812 | .806 | .820 |

Table A.7: Baseline Specification Using Rice Prices

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | Monetary Lending (¥/hectare) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| post* paddy | -18.820*** | -15.960** | -20.427*** | -18.820*** | -22.221*** |
| | ( 6.769) | (6.282) | ( 5.127) | (6.769) | (7.165) |
| Factory FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| Prefecture Controls | N | N | N | N | Y |
| Mill Controls | N | N | Y | N | N |
| Prefecture*Year FE | N | Y | Y | N | N |
| Mill Trends | N | N | N | Y | Y |
| N Mills | 38 | 38 | 33 | 38 | 33 |
| N Observations | 360 | 360 | 291 | 360 | 291 |
| $R^2$ | .829 | .877 | .878 | .829 | .851 |

Table A.8: Baseline specification with Prefecture-Year Fixed Effects and Linear Mill Trends

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | Log Total Lending & Inputs | Log Monetary Loans | Log Inputs Provided |
|---|---|---|---|
| | (1) | (2) | (3) |
| paddy*1929 | -.072 | -.193 | .126 |
| | (.169) | (.230) | (.197) |
| paddy*1930 | .045 | .068 | .082 |
| | (.139) | (.200) | (.144) |
| paddy*1932 | -.539** | -.896** | -.286 |
| | (.271) | (.411) | (.220) |
| paddy*1933 | -.394* | -.924** | -.008 |
| | (.216) | (.394) | (.205) |
| paddy*1934 | -.395* | -.829** | -.469 |
| | (.234) | (.465) | (.348) |
| paddy*1935 | -.533* | -1.057** | -.139 |
| | (.275) | (.475) | (.250) |
| paddy*1936 | -.517 | -1.018* | -.101 |
| | (.321) | (.552) | (.271) |
| paddy*1937 | -.143 | -.494 | .039 |
| | (.299) | (.521) | (.302) |
| paddy*1938 | -.018 | -.424 | .237 |
| | (.293) | (.488) | (.333) |
| paddy*1939 | -.062 | -.517 | .305 |
| | (.266) | (.493) | (.280) |
| Factory FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Prefecture Trends | Y | Y | Y |
| N Mills | 38 | 38 | 38 |
| N Observations | 360 | 360 | 360 |
| $R^2$ | .841 | .829 | .830 |

Table A.9: Time-varying Treatment Effects

**Notes:** The dependent variables are expressed as the total amount divided by the area on which sugarcane is being cultivated in the same year. The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | All Fields | | Paddy Fields | | Dry Fields | |
|---|---|---|---|---|---|---|
| | (Log Area in Hectares) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -.081 | -.070 | -.470*** | -.511*** | .125** | .215*** |
| | (.064) | (.077) | (.172) | (.169) | (.061) | (.058) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | Y | N | Y | N | Y |
| Mill Controls | N | Y | N | Y | N | Y |
| N Mills | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 362 | 293 | 362 | 293 | 362 | 293 |
| $R^2$ | .913 | .906 | .811 | .810 | .848 | .856 |
| Mean | 1649.189 | | 574.787 | | 1074.40 | |

Table A.10: The Effect on the Area Cultivated by Field Type

**Notes:** The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | All Fields | | Paddy Fields | | Dry Fields | |
|---|---|---|---|---|---|---|
| | (Log Ton/Hectares) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -.077*** | -.071* | -.115** | -.144* | -.069*** | -.081** |
| | (.026) | (.038) | (.052) | (.085) | (.024) | (.033) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | N | Y | N | Y | N | Y |
| Mill Controls | N | Y | N | Y | N | Y |
| N Mills | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 362 | 293 | 362 | 293 | 362 | 293 |
| $R^2$ | .607 | .613 | .327 | .334 | .788 | .823 |
| Mean | 65.972 | | 75.851 | | 58.461 | |

Table A.11: The Effect on Yields by Field Type

**Notes:** The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

,

| | Cane Input Log '00 tons | Sugar Output Log tons | Sugar Yield % | Harvest Duration Days | Share of Days Inactive | Capacity Log Tons/Day |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -.035 | -.022 | .346 | -3.582 | 2.18** | -.015 |
| | ( .083) | (.078) | (.486) | (4.642) | (1.054) | (.049) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Controls | Y | Y | Y | Y | Y | Y |
| Mill Controls | Y | Y | Y | Y | Y | Y |
| N Mills | 38 | 33 | 38 | 33 | 38 | 33 |
| N Observations | 293 | 293 | 293 | 291 | 293 | 293 |
| $R^2$ | .848 | .845 | .694 | .714 | .977 | .837 |
| Mean | 1429 | 1841 | 12.10 | 133.89 | 43.61 | 917.24 |

Table A.12: Production Outcomes

**Notes:** The independent variable has been normalised such that one unit equals one standard deviation. Prefecture controls include Prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

| | All Fields | | Paddy Fields | | Dry Fields | |
|---|---|---|---|---|---|---|
| | Log hectare | Log Yields (ton/h) | Log hectare | Log Yields (ton/h) | Log hectare | Log Yields(ton/h) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post* paddy | -.155 | .012 | -.113 | .025 .841 | -.073 | |
| | (.130) | (.038) | (.128) | (.038) | (1.078) | (.062) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Controls× post | Y | Y | Y | Y | Y | Y |
| N Mills | 33 | 33 | 33 | 33 | 33 | 33 |
| N Observations | 292 | 292 | 234 | 234 | 266 | 266 |
| $R^2$ | .912 | .753 | .880 | .734 | .756 | .727 |
| Mean | 455.3 | 71.55 | 192.2 | 130.5 | 263.2 | 103.2 |

**Notes:** Prefecture controls include prefecture population, the population employed in agriculture, cattle owned and total arable land. Mill controls: age,parent company equity, number of factories owned by the parent company and total size of the command area - all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. Column(3) F-test of excluded instruments is 17.52. ***p>0.001 **p>0.05 *p>0.10

Table A.13: Mill Cultivation of Sugarcane

| | Fertilizer | | | | Seeds | |
|---|---|---|---|---|---|---|
| | Yen per hectare cultivated with cane | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post× paddy | 2.556 | 2.163 | 4.760 | -1.367 | .546 | 4.936 |
| | (3.496) | (3.661) | ( 4.528) | (2.051) | (2.471) | (3.028) |
| Factory & Year FE | N | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | N | Y | Y | N |
| Controls× post | N | Y | Y | N | Y | Y |
| Prefecture × Year FE | N | N | Y | N | N | Y |
| N Mills | 38 | 33 | 33 | 38 | 33 | 33 |
| N Observations | 358 | 291 | 291 | 358 | 290 | 290 |
| $R^2$ | .796 | .853 | .864 | .766 | .745 | .810 |
| Mean | | 95.99 | | | 13.88 | |

**Notes:** Prefecture controls include prefecture population, the population employed in agriculture, number of cattle owned and total land under cultivation. Mill controls are age as well as parent company equity, the number of factories owned by the parent company and total size of the command area, which are all interacted with a post-1931 dummy. All standard errors are clustered at the factory level. ***p>0.001 **p>0.05 *p>0.10

Table A.14: Effect on Inputs Provided

| | Total Lending by Mills to Farmers Yen per hectare cultivated with cane | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post×paddy×Capital | .027 | -.023 | .096 | | | |
| | (.184) | (.119) | (.096) | | | |
| post× Capital | .384 | .186 | -.259 | | | |
| | (.600) | (.521) | (.474) | | | |
| post×paddy× # of Factories | | | | -.102 | -.335 | .246 |
| | | | | (.798) | (.503) | (.384) |
| post× # of Factories | | | | 2.021 | 1.244 | -.639 |
| | | | | (2.040) | (1.759) | (1.759) |
| post× paddy | -28.323*** | -26.218*** | -22.144*** | -26.260*** | -26.698*** | -21.383*** |
| | (9.869) | (9.098) | (4.770) | (9.254) | (9.005) | (4.892) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | N | Y | Y | Y |
| Prefecture×Year FE | N | N | Y | N | N | Y |
| N Mills | 29 | 29 | 29 | 29 | 29 | 29 |
| N Observations | 305 | 272 | 310 | 272 | 309 | 246 |
| $R^2$ | .841 | .829 | .794 | .815 | .891 | .799 |

**Notes:** Capital is measured in the year 1921 and expressed in million Yens. All standard errors are clustered at the factory level. Column(3) F-test of excluded instruments is 17.52. ***p>0.001 **p>0.05 *p>0.10

Table A.15: Heterogeneous Effects by Size

| | Total Lending & Inputs | | Monetary Loans | | Inputs Provided | |
|---|---|---|---|---|---|---|
| | Logged Value | *Yen*/hectare | Logged Value | *Yen*/hectare | Logged Value | *Yen*/hectare |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| post×paddy×court | .1602* | 14.881 | .318* | 15.756* | .126 | -4.105 |
| | (.097) | ( 11.979) | (.179) | (9.318) | (.091) | (9.861) |
| post× paddy | -.296** | -44.161** | -.938* | -46.802*** | -.414 | 8.941 |
| | (.136) | ( 17.841) | (.527) | ( 13.826) | (.255) | (12.660) |
| post× court | -.498* | -24.12** | -.650** | -31.798 | -.177 | 20.809 |
| | (.283) | (36.442) | (.256) | (28.741) | (.138) | (18.661) |
| Factory FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Prefecture Trends | Y | Y | Y | Y | Y | Y |
| N Mills | 29 | 29 | 29 | 29 | 29 | 29 |
| N Observations | 305 | 272 | 310 | 272 | 309 | 246 |
| $R^2$ | .841 | .829 | .794 | .815 | .891 | .799 |
| Mean | 209.74 | 209.74 | 102.93 | 102.93 | 106.89 | 106.89 |

**Notes:** All standard errors are clustered at the factory level. Column(3) F-test of excluded instruments is 17.52. ***p>0.001 **p>0.05 *p>0.10

Table A.16: Heterogeneous Effects by Presence of Court

## A.2 Figures

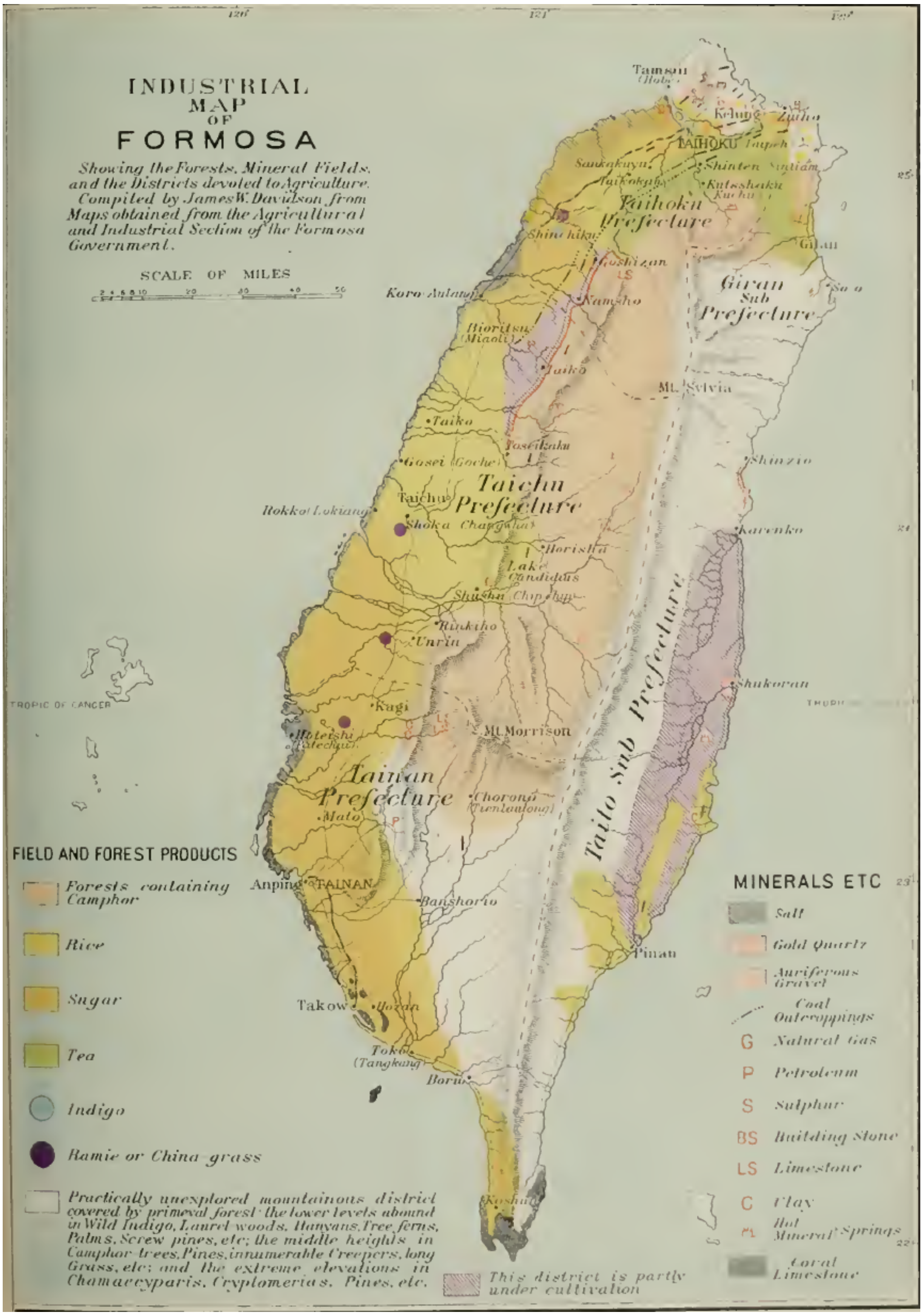


Figure A.1: Agricultural Activity in Taiwan 1905

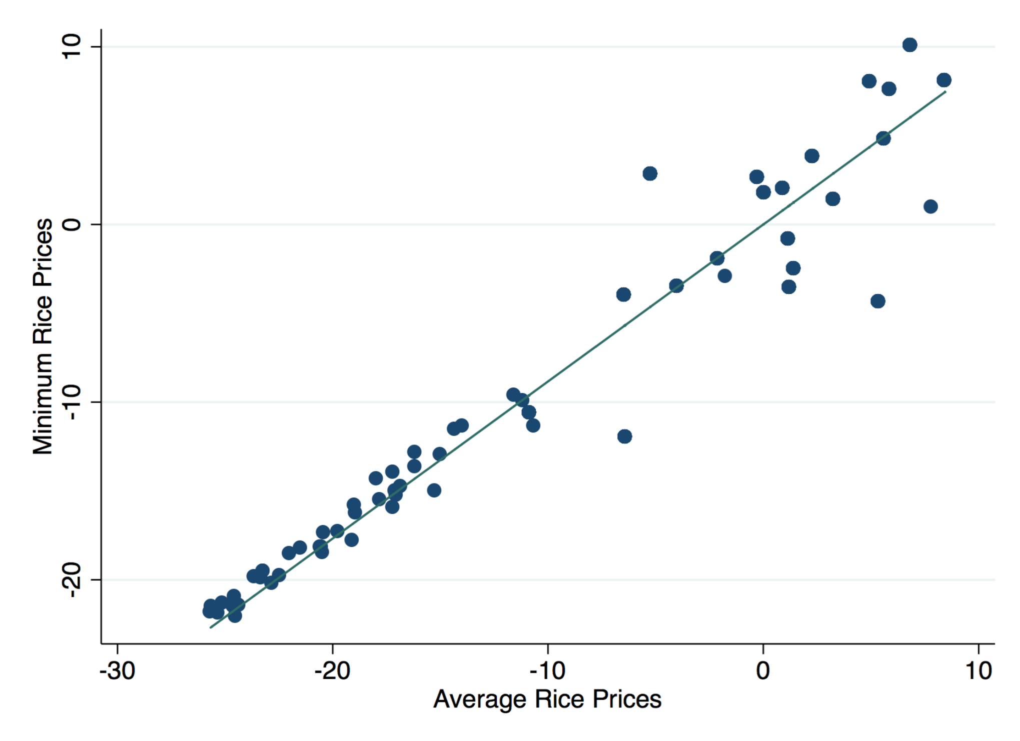


Figure A.2: Correlation between Average and Minimum Rice Prices

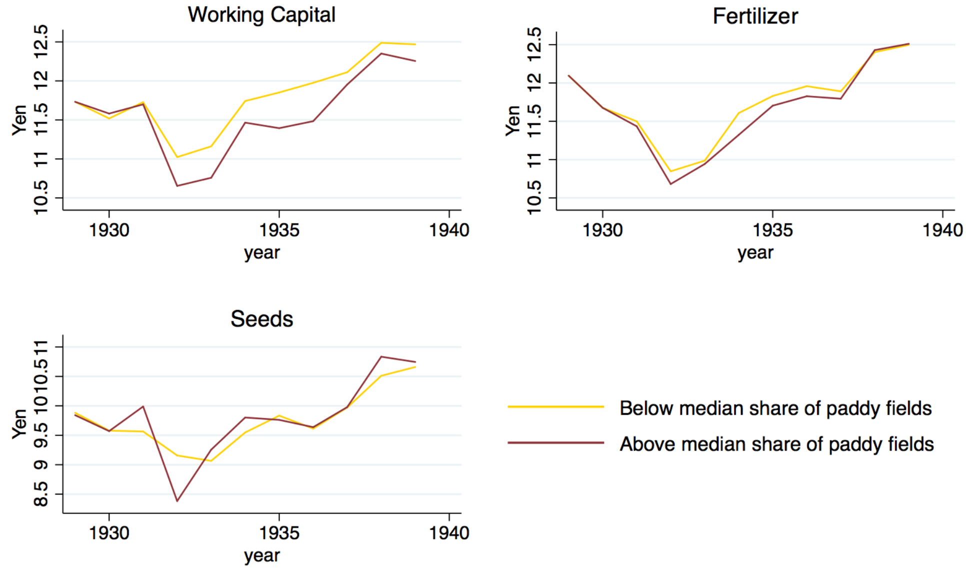


Figure A.3: Average Value of Loans and Inputs Provided

The total value of loans and inputs for mills with less than median share of paddy fields is normalised to equal the other group in the year 1929. Values are expressed in loged Yen.

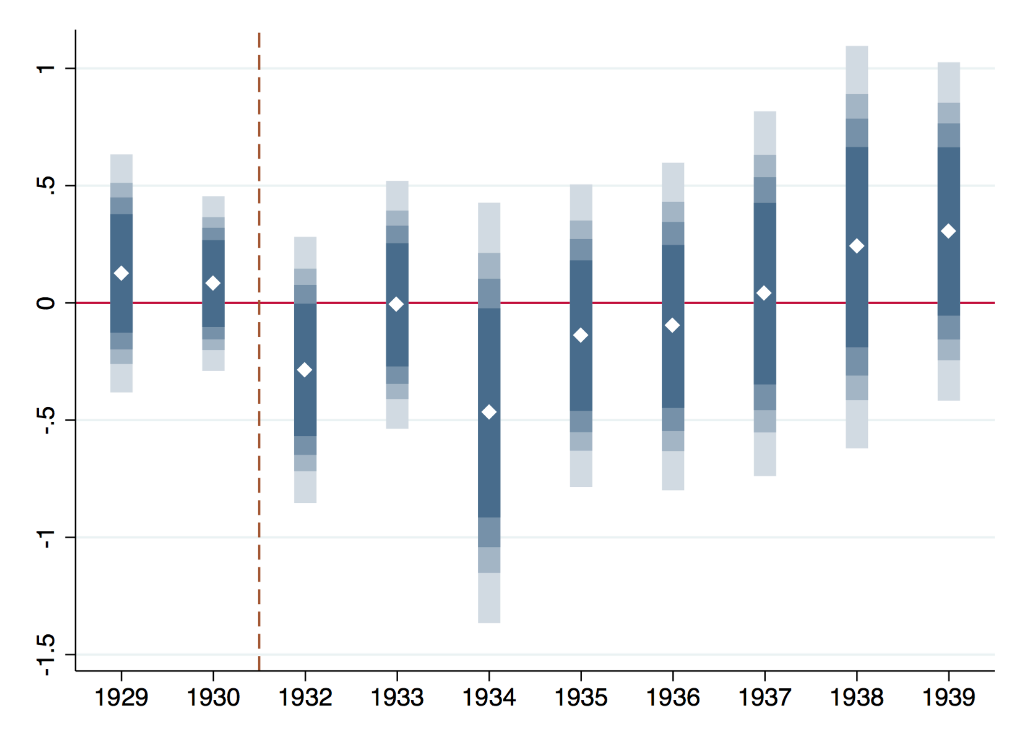


Figure A.4: Time-varying Treatment Effect Estimates on Log Inputs Provided

**Notes:** The outcome variable is the log value of all inputs provided. Confidence intervals shown are at the 99%, 95%, 90% and 80% levels. The reference year is 1931.

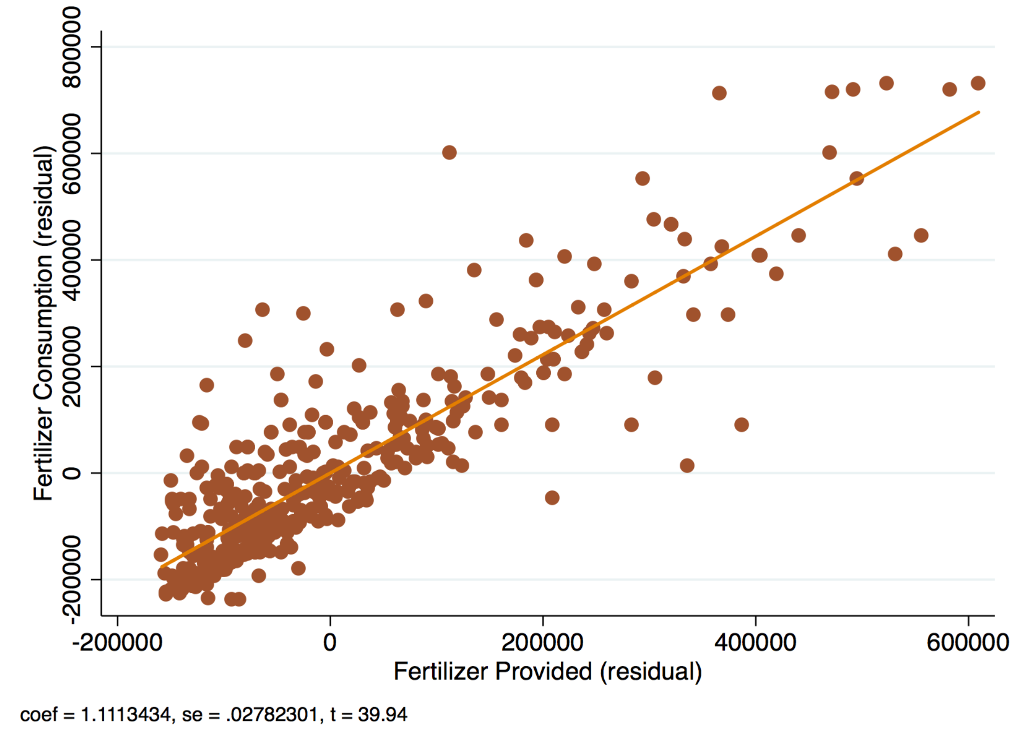


Figure A.5: Correlation Between Fertiliser Provided and Actual Consumption

**Notes:** Both variables are expressed in Japanese Yen.

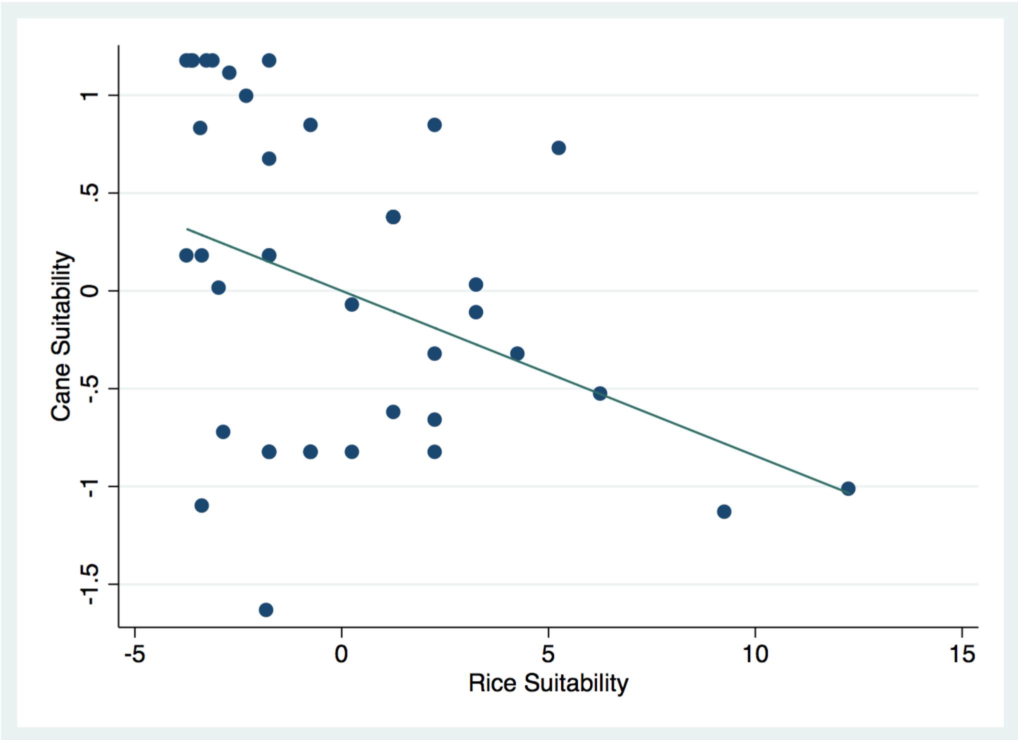


Figure A.6: Correlation between Cane and Rice Suitability

# Appendix B

# The Benefits of the Bamboo Network in International Trade

## B.1 Profitability (TFPR)

In addition to analysing the effect of better access to the American Chinese network on exports, we also investigate the effect on a number of other firm variables. While most of these are easily observed in the Annual Survey of Industrial Enterprises, we need to construct our own measure of total factor productivity, as described in this section.

We do not have information about quantities produced, and instead rely on revenue data; thus, we are unable to accurately measure total factor productivity and instead are limited to estimating total *revenue* productivity. Revenue productivity however is only an imperfect approximation of actual total factor productivity: firms can have a high factor productivity because they are more efficient, or because they have higher idiosyncratic demand and thus are able to charge higher prices.

We model production with a simple Cobb-Douglas production function:

$$Y_{f,i,c} = A_{f,i,c} K_{f,i,c}^{\alpha_i^k} L_{f,i,c}^{\alpha_i^l} M_{f,i,c}^{\alpha_i^i} \tag{B.1}$$

Where $Y_{f,i,c}$ is output produced by firm $f$ in industry $i$ in county $c$, $K_{f,i,c}$ is capital, $L_{f,i,c}$ is labour and $M_{f,i,c}$ are all intermediate products used in production. We then follow the Foster et al. (2008) and calculate firm level total factor productivity as:

$$tfpr_{f,i,c} = y_{f,i,c} - \alpha_i^k k_{f,i,c} - \alpha_i^l l_{f,i,c} - \alpha_i^; m_{f,i,c} \tag{B.2}$$

where the lower-case letters indicate logarithms of establishment-level TFPR, value of output, labor inputs, capital stock and intermediate inputs respectively, and $\alpha_j(j = \{l, k, m\})$ are the factor elasticities for the relevant inputs. Output is measured as total value of output produced; capital is measured as the net value of all fixed assets, while labour input is measured as the number of employees. Intermediate inputs are measured as the total value of all intermediate industrial inputs.

It is important to note that the amount of inputs used is clearly endogenous to the firm specific productivity level. Thus we cannot identify the input elasticities for each firm. Instead we use average cost shares of inputs in each industry to calculate the elasticities. The cost shares for labour and materials are calculated using expenditure from the survey at the industry level, while the cost share of capital is calculated as the average amount of capital stocks times the respective capital rental rates for each firm's corresponding two digit industry, taken from US data in the absence such data being available for China.

## B.2 Creating Industry Exposure Measure

### B.2.1 Linking Industries in China to the U.S.

In this paper, we suppose that a Chinese firm $f$ in industry $i$ can be exposed to the Cantonese U.S. network in three different ways: through American-Cantonese workers employed in the same industry $i$ (referred to as "same industry"), through workers employed in a retail or wholesale sector that sell goods produced by industry $i$ ("retail and wholesale") and finally though workers active in other downstream manufacturing sectors that use industry $i$'s products as intermediate inputs ("manufacturing").

Calculating the number of ethnically Cantonese American workers employed in the *same industry* is relatively straightforward. The main challenge is converting the industry classification used in the 2000 U.S.

Census to the classifications used in our Chinese data. We start by converting the U.S. data to the International Standard Industrial Classification (ISIC), which allows us to identify industries up to the four-digit level, using conversion tables provided by the United States Census Bureau. However, while the Chinese industry classification scheme is modeled after the ISIC system, it is not identical and, to our knowledge, there is no official conversion. Thus we develop our own conversion scheme, by matching industries by their description. Despite also being reported at the four-digit level, the number of industries in the Chinese classification is larger than in the ISIC. Overall, we are able to match 687 out of 709 Chinese industries to 189 ISIC industries.

In order to calculate our second measure of industry exposure, the number of workers in a downstream retail or wholesale industry, we need to link Chinese industries to American retail industries. Ideally, we would make use of information how much each American retail or wholesale industry imports from each Chinese industry. As we do not have access to this information, we instead match manufacturing to retail and wholesale industries using industry descriptions. For more details on this process see Appendix B.2.2.

Thirdly, we match industries in China with American manufacturing industries that are likely to use the Cantonese firms' products as intermediate inputs. In order to establish which firm purchases which inputs and thus linking Chinese industries to related downstream industries, we use the information provided by the Input-Output tables compiled by the Bureau of Economic Analysis for the year 2002. These tables give detailed information of the inputs purchased for each six digit industry according to the North American Industry Classification. We thus calculate for each industry the weighted average of Cantonese workers that purchases its products according to the share of total sales of industry $i$.

### B.2.2 Chinese Manufacturing Industries to U.S. Wholesale and Retail Industries

To calculate the measure of industry exposure described in Section 4.1 we need to match manufacturing industries in China with their likely wholesale and retail counterpart in the U.S. Ideally, to perform this matching we would have information about imports and exports that reveal the top industries which import manufacturing data.

In the absence of that, we need to impute which manufacturing industries match with which retail industries. We achieve this by first isolating key words in the description of the manufacturing industry in China. As a next step, we then match these key words to the description of the corresponding NAICS retail and wholesale industry. For example, in the case of a tobacco and cigarette manufacturer in China, we then conduct a search for the key words in the NAICS database for retail and wholesale industries whose description contained related words to Tobacco. In this case we link tobacco production to the wholesale industry 424940 "Tobacco and Tobacco Product Merchant Wholesalers" and 424590 "Other Farm Product Raw Material Merchant Wholesalers" which includes "Auction markets for tobacco" in their description, as well as the retail industry 453991 "Tobacco Stores". Of course these are imperfect measures of the retailers and wholesalers truly stocking these products, as we usually exclude generalised retailers.

In this way our matching may be subject to measurement error. In an attempt to reduce it, when we construct the industry exposure measure we take the average number of Chinese workers that work in the industries which are matched to each Chinese industry code.

## B.3 Tables

| | Number of Immigrants | Percentage |
|---|---|---|
| Taishan | 44,131 | 47.7 |
| Xinhui | 13,858 | 15.0 |
| Kaiping | 13,350 | 14.4 |
| Enping | 3,754 | 4.1 |
| Heshan | 2,574 | 2.8 |
| **Siyi** | **77,667** | **84.0** |
| Panyu | 6,415 | 6.9 |
| Nanhai | 480 | 0.5 |
| Shunde | 420 | 0.5 |
| **Sanyi** | **7,315** | **7.9** |
| Zhongshan | 5,899 | 6.4 |
| Other | 1607 | 1.7 |

**Total: 92488**

Table B.1: Origin of Canadian-Chinese by County in China

**Notes:** Data from Yu (2011).

| | Mean | Median | SD | Min | Max | N |
|---|---|---|---|---|---|---|
| Export Status | .500 | 0 | .500 | 0 | 1 | 34,558 |
| Export Value ('000 RMB) | 37311.29 | 0 | 502314.9 | 0 | 1.50e+07 | 34,525 |
| | | | **All Firms** | | | |
| Employment (N. workers) | 288.530 | 121 | 816.850 | 1 | 71915 | 34,525 |
| Share of High Skilled Workers(%) | .038 | .008 | .089 | 0 | 1 | 34,525 |
| Total Wages ('000 RMB) | 4470.353 | 1478 | 29928.25 | 6 | 4158034 | 34,525 |
| Management Expenses ('000 RMB) | 3580.832 | 979 | 39077.91 | 0 | 5078518 | 34,525 |
| Profits ('000 RMB) | 4108.157 | 226 | 83596.41 | -278790 | 7728064 | 34,525 |
| Output ('000 RMB) | 85368.06 | 18540 | 938114.4 | 0 | 1.09e+08 | 34,525 |
| Domestic Sales ('000 RMB) | 83475.68 | 18008 | 925507.6 | 0 | 1.09e+08 | 34,525 |
| Fixed Assets ('000 RMB) | 24737.29 | 2932 | 551633.3 | 0 | 9.60e+07 | 34,525 |
| Total Capital ('000 RMB) | 19458.72 | 3600 | 277759.9 | 0 | 4.87e+07 | 34,525 |
| Foreign Capital Share (%) | .104 | 0 | .296 | 0 | 1 | 34,379 |
| State Owned Dummy | .051 | 0 | .219 | 0 | 1 | 34,525 |
| | | | **Exporting Firms** | | | |
| Employment (N. workers) | 439.233 | 200 | 1066.735 | 2 | 71915 | 17,232 |
| Share of High Skilled Workers(%) | .032 | .008 | .070 | 0 | 1 | 17,232 |
| Total Wages ('000 RMB) | 6627.220 | 2398 | 27344.32 | 24 | 2204273 | 17,232 |
| Management Expenses ('000 RMB) | 5129.092 | 1387.5 | 54399.75 | 0 | 5078518 | 17,232 |
| Profits ('000 RMB) | 5509.688 | 260 | 94274.87 | -246506 | 7728064 | 17,232 |
| Output ('000 RMB) | 119333.8 | 23501 | 975514.4 | 0 | 7.30e+07 | 17,232 |
| Domestic Sales ('000 RMB) | 42492.64 | 147.5 | 517657.9 | 1 | 3.97e+07 | 17,232 |
| Fixed Assets ('000 RMB) | 25285.13 | 4150.5 | 154693.3s | 0 | 9111732 | 17,232 |
| Total Capital ('000 RMB) | 24297.66 | 6626.5 | 110130.8 | 0 | 8842600 | 17,232 |
| Foreign Capital Share (%) | .050 | 0 | .199 | 0 | 1 | 17,232 |
| State Owned Dummy | .023 | 0 | .153 | 0 | 1 | 17,232 |

Table B.2: Descriptive Statistics: Firms Characteristics

**Notes:** This table shows the descriptive statistics of the main variables used in this paper. When applicable the data is shown in 2004 RMB, at which point 1USD =8.28 RMB. Source: 2004 Annual Survey of Industrial Enterprises.

| | Mean | Median | SD | Min | Max | N |
|---|---|---|---|---|---|---|
| | **Cultural Exposure** | | | | | |
| Sending Counties Dummy | .144 | 0 | .351 | 0 | 1 | 34,525 |
| Cantonese Counties Dummy | .681 | 1 | .466 | 0 | 1 | 34,525 |
| | **Industry Exposure** | | | | | |
| Cantonese Workers Retail and Wholesale | 253.311 | 144.763 | 285.397 | 2.367 | 2789.528 | 31,026 |
| Cantonese Workers Downstream Manufacturing | 4112.293 | 2109.71 | 6210.863 | 22 | 25698.23 | 34,083 |
| Cantonese Workers Same Industry | 283.737 | 118.306 | 412.163 | .322 | 8462.154 | 34,112 |

Table B.3: Descriptive Statistics: Cultural and Industry Exposure

**Notes:** This table shows the descriptive statistics of the main independent variables variables used in this paper. Sources: 2004 Annual Survey of Industrial Enterprises.

| | Cantonese Workers |
|---|---|
| Restaurants and Other Food Services | 47,199 |
| Colleges and Universities | 26,132 |
| Hospitals | 24,494 |
| Elementary and Secondary Schools | 20,436 |
| Electronic Components and Products Manufacturing | 14,070 |
| Other Information Services | 13,396 |
| Computer systems design and related services | 12,262 |
| Construction | 11,483 |
| Grocery Stores | 11,372 |
| Securities, commodities, funds, trusts, and other financial investments | 10,739 |

Table B.4: Top 10 U.S. 4 Digit Industries by Number of Cantonese Workers

**Notes:** U.S. 2000 Population Census data.

| | Cantonese Workers |
|---|---|
| Carpets and rugs manufacturing | 14 |
| Logging | 18 |
| Tobacco Manufacturing | 22 |
| Railroad rolling stock manufacturing | 22 |
| Support activities for agriculture and forestry | 24 |
| Tire manufacturing | 24 |
| Farm supplies wholesalers | 25 |
| Not specified metal industries | 37 |
| Other transportation equipment manufacturing | 38 |
| Structural clay product manufacturing | 41 |

Table B.5: Last 10 U.S. 4 Digit Industries by Number of Cantonese Workers

**Notes:** U.S. 2000 Population Census data.

| | Retail and Wholesale | | Manufacturing | | Same Industry | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .045* | .029** | | | | |
| | (.026) | (.012) | | | | |
| Workers Related Retail | .094*** | | | | | |
| | (.013) | | | | | |
| Workers Downstream Manufacturing * Sending | | | .057*** | .030*** | | |
| | | | (.008) | (.004) | | |
| Workers Downstream Manufacturing | | | .039*** | | | |
| | | | (.007) | | | |
| Workers Same Industry * Sending | | | | | .061*** | .030*** |
| | | | | | (.017) | (.009) |
| Workers Same Industry | | | | | .042** | |
| | | | | | (.017) | |
| Sending Counties | -.177*** | | -.184*** | | -.175*** | |
| | (.022) | | (.019) | | (.019) | |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | N | Y | N | Y | N | Y |
| County FE | N | Y | N | Y | N | Y |
| N of observations | 22,413 | 22,413 | 24,069 | 24,069 | 24,043 | 24,043 |
| R-Squared | 0.0762 | 0.2878 | 0.0458 | 0.2927 | 0.0443 | 0.2918 |

Table B.6: Extensive Margin: Probability of Exporting

**Notes:** The dependent variable is a binary variable indicating firms export status. Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The variables denoted as *workers* refers to the number of Cantonese workers in each 4-digit industries in the U.S. The coefficients of the variables *network* and *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .029*** | | | .138*** | | |
| | (.010) | | | (.040) | | |
| Workers Downstream Manufacturing* Sending | | .030*** | | | .057* | |
| | | (.011) | | | (.033) | |
| Workers Same Industry * Sending | | | .030** | | | .079** |
| | | | (.014) | | | (.040) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,393 | 24,041 | 24,017 | 11,259 | 11,777 | 11,777 |
| R-Squared | 0.2871 | 0.2919 | 0.2911 | 0.1501 | 0.1544 | 0.1544 |

Table B.7: Baseline Specification - Standard Errors Clustered at County Level

**Notes:** Standard errors in parenthesis and clustered at the county level. Controls are at the county level and include total county population, emigration (%), and university attendance (%). The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Related Retail×Cantonese | .023*** | | | .080*** | | |
| | (.008) | | | (.030) | | |
| Workers Downstream Manufacturing×Cantonese | | .017*** | | | .047** | |
| | | (.003) | | | (.019) | |
| Workers Same Industry×Cantonese | | | .007 | | | .022 |
| | | | (.010) | | | (.044) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,393 | 24,041 | 24,017 | 11,259 | 11,777 | 11,777 |
| R-Squared | 0.2872 | 0.2917 | 0.2908 | 0.1500 | 0.1545 | 0.1542 |

Table B.8: Exports - Network Exposure for Cantonese Counties

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. In these regressions, network exposure is constructed as *industry exposure* times a dummy variable which indicates whether a county's main language belongs to the Cantonese language group. The coefficients of the variables defined as *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .038** | | | .159*** | | |
| | (.015) | | | (.043) | | |
| Workers Downstream Manufacturing* Sending | | .036*** | | | .062*** | |
| | | (.004) | | | (.024) | |
| Workers Same Industry * Sending | | | .037*** | | | .084** |
| | | | (.010) | | | (.035) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Controls×Industry FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,234 | 23,861 | 23,837 | 11,083 | 11,572 | 11,572 |
| R-Squared | 0.3235 | 0.3301 | 0.3293 | 0.2028 | 0.2092 | 0.2093 |

Table B.9: Baseline Specification with County Controls Interacted with Industry Fixed Effects

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. Controls are at the county level and include total county population, emigration (%), and university attendance (%). The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Retail and Wholesale | | Manufacturing | | Same Industry | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .148*** | .138*** | | | | |
| | (.041) | (.037) | | | | |
| Workers Related Retail | .050** | | | | | |
| | (.024) | | | | | |
| Workers Same Workers * Sending | | | .086*** | .057*** | | |
| | | | (.021) | (.020) | | |
| Workers Downstream Manufacturing | | | -.019 | | | |
| | | | (.020) | | | |
| Workers Same Industry * Sending | | | | | .052 | .079** |
| | | | | | (.051) | (.032) |
| Workers Same Industry | | | | | .054 | |
| | | | | | (.039) | |
| Sending Counties | -.328*** | | -.250*** | | -.210*** | |
| | (.094) | | (.079) | | (.080) | |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | N | Y | Y | N | Y | Y |
| County FE | N | Y | Y | N | Y | Y |
| N of observations | 11,314 | 11,314 | 11,834 | 11,834 | 11,834 | 11,834 |
| R-Squared | 0.0185 | 0.1561 | 0.0146 | 0.1599 | 0.0157 | 0.1599 |

Table B.10: Intensive Margin: Export Value

**Notes:** The dependent variable is log of export value. Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The variables denoted as *workers* refers to the number of Cantonese workers in each 4-digit industries in the U.S. The coefficients of the variables *network* and *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Related Retail×Sending | .022* | | | .112*** | | |
| | (.013) | | | (.039) | | |
| Workers Downstream Manufacturing×Sending | | .025*** | | | .042* | |
| | | (.004) | | | (.021) | |
| Workers Same Industry×Sending | | | .029*** | | | .076** |
| | | | (.008) | | | (.035) |
| Workers Related Retail×Cantonese | .019*** | | | .061* | | |
| | (.007) | | | (.032) | | |
| Workers Downstream Manufacturing×Cantonese | | .013*** | | | .039** | |
| | | (.004) | | | (.020) | |
| Workers Same Industry×Cantonese | | | .002 | | | .011 |
| | | | (.010) | | | (.051) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,393 | 24,041 | 24,017 | 11,259 | 11,777 | 11,777 |
| R-Squared | 0.2874 | 0.2920 | 0.2911 | 0.1505 | 0.1546 | 0.1544 |

Table B.11: Exports - Heterogeneous Effects for Sending Counties

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .032*** | | | .146*** | | |
| | (.012) | | | (.034) | | |
| Workers Downstream Manufacturing* Sending | | .029*** | | | .072*** | |
| | | (.004) | | | (.019) | |
| Workers Same Industry * Sending | | | .028*** | | | .102*** |
| | | | (.009) | | | (.030) |
| Foreign Capital (%) | .035*** | .035*** | .035*** | .320*** | .317*** | .317*** |
| | (.006) | (.006) | (.006) | (.026) | (.025) | (.025) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 25,650 | 27,473 | 27,449 | 13,947 | 14,576 | 14,576 |
| R-Squared | 0.2794 | 0.2857 | 0.2849 | 0.1901 | 0.1910 | 0.1911 |

Table B.12: Control for Foreign Capital

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *network* and *foreign capital* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Export Value | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .146*** | .180*** | | | | |
| | (.037) | (.040) | | | | |
| Workers Downstream Manufacturing* Sending | | | .058*** | .082*** | | |
| | | | (.020) | (.023) | | |
| Workers Same Industry * Sending | | | | | .087*** | .121*** |
| | | | | | ( .032) | (.035) |
| Foreign Capital (%) | | .026*** | | .320*** | | .319*** |
| | | (.027) | | (.027 ) | | (.027) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| County Controls×Industry FE | N | Y | N | Y | N | Y |
| Domestic Firms Only | Y | N | Y | N | Y | N |
| N of observations | 11,641 | 14,176 | 11,641 | 14,176 | 11,641 | 14,176 |
| R-Squared | 0.6150 | 0.6442 | 0.6184 | 0.6473 | 0.6246 | 0.6088 |

Table B.13: Exports Adjusted by Share of Industry Exports to the US Vs. World

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. Controls are at the county level and include total county population, emigration (%), and university attendance (%). The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .028 | | | .129*** | | |
| | (.017) | | | (.041) | | |
| Workers Downstream Manufacturing* Sending | | .036*** | | | .082*** | |
| | | (.004) | | | (.020) | |
| Workers Same Industry * Sending | | | .038*** | | | .097*** |
| | | | (.008) | | | (.031) |
| Non-Cantonese Workers Related Retail×Sending | .002 | | | .015 | | |
| | (.010) | | | (.035) | | |
| Non-Cantonese Workers Downstream Manufacturing×Sending | | -.025*** | | | -.160*** | |
| | | (.008) | | | (.053) | |
| Non-Cantonese Workers Same Industry×Sending | | | -.029* | | | -.139 |
| | | | (.017) | | | (.086) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,393 | 24,041 | 24,017 | 11,259 | 11,777 | 11,777 |
| R-Squared | 0.2871 | 0.2920 | 0.2912 | 0.1502 | 0.1548 | 0.1545 |

Table B.14: Control for Industry Size

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. In these regressions, network exposure is constructed as *industry exposure* times a dummy variable which indicates whether a county's main language belongs to the Cantonese language group. The coefficients of the variables defined as *network* and *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Log Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | -.007 | | | .281 | | |
| | (.022) | | | (.207) | | |
| Workers Retail* Sending × Differentiated | .043* | | | -.142 | | |
| | (.025) | | | (.211) | | |
| Workers Downstream Manufacturing* Sending | | .005 | | | .058*** | |
| | | (.039) | | | (.021) | |
| Workers Downstream Manufacturing* Sending × Differentiated | | .023 | | | .036** | |
| | | (.040) | | | (.016) | |
| Workers Same Industry * Sending | | | -.030 | | | .130 |
| | | | (.024) | | | (.367) |
| Workers Same Industry * Sending × Differentiated | | | .060** | | | -.038 |
| | | | (.026) | | | (.368) |
| Sending × Differentiated | .004 | .014 | .004 | .203 | .157 | .176 |
| | (.024) | (.029) | (.024) | (.244) | (.139) | (.183) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 25,650 | 27,473 | 27,449 | 13,947 | 14,576 | 14,576 |
| R-Squared | 0.2751 | 0.2813 | 0.2805 | 0.1446 | 0.1473 | 0.1472 |

Table B.15: Heterogeneous Effects for Differentiated Goods

**Notes:** Differentiated goods are identified using the classification scheme published by Rauch (1999), using the conservative classification. Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | | Export Value | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Network Retail (Self-employed) | .010 | | | | .152*** | | | |
| | (.010) | | | | (.043) | | | |
| Network Manufacturing (Self-employed) | | .030** | | | | .059* | | |
| | | (.012) | | | | (.034) | | |
| Network Retail (Wage Workers) | | | .030*** | | | | .136*** | |
| | | | (.010) | | | | (.039) | |
| Network Manufacturing (Wage Workers) | | | | .031*** | | | | .056* |
| | | | | (.012) | | | | (.033) |
| Age | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y |
| N of observations | 19,145 | 24,041 | 22,393 | 24,041 | 10,246 | 11,777 | 11,259 | 11,777 |
| R-Squared | 0.2754 | 0.2919 | 0.2871 | 0.2919 | 0.1413 | 0.1544 | 0.1501 | 0.1544 |

Table B.16: Self-employed vs. Wage Workers

**Notes:** Standard errors in parenthesis and clustered at the county level. The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Domestic Firms | | | Exporting Firms | | | Non-exporting Firms | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Workers Retail* Sending | -.003 | | | -.009 | | | .005 | | |
| | (.007) | | | (.011) | | | (.015) | | |
| Workers Downstream Manufacturing* Sending | | -.005 | | | -.016*** | | | .010 | |
| | | (.004) | | | (.005) | | | (.012) | |
| Workers Same Industry * Sending | | | -.003 | | | -.020*** | | | .015 |
| | | | (.007) | | | (.007) | | | (.013) |
| Age | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| N of observations | 22,147 | 23,627 | 23,627 | 11,196 | 11,731 | 11,731 | 10,886 | 11,829 | 11,829 |
| R-Squared | 0.1479 | 0.1495 | 0.1495 | 0.1372 | 0.1392 | 0.1392 | 0.1767 | 0.1764 | 0.1764 |

Table B.17: TFPR

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Log Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .032** | | | .131*** | | |
| | (.015) | | | (.042) | | |
| Workers Retail* Sending × High Tech | -.009 | | | .062 | | |
| | (.021) | | | (.122) | | |
| Workers Downstream Manufacturing* Sending | | .036*** | | | .051** | |
| | | (.004) | | | (.023) | |
| Workers Downstream Manufacturing* Sending × High Tech | | .031 | | | .184 | |
| | | (.060) | | | (.400) | |
| Workers Same Industry * Sending | | | .033*** | | | .066** |
| | | | (.011) | | | (.032) |
| Workers Same Industry * Sending × High Tech | | | .004 | | | .122 |
| | | | (.032) | | | (.193) |
| Sending × High Tech | .039 | .043 | .041* | -.063 | -.107 | -.108 |
| | (.026) | (.029) | (.024) | (.206) | (.217) | (.157) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 22,393 | 24,041 | 24,017 | 11,259 | 11,777 | 11,777 |
| R-Squared | 0.2872 | 0.2921 | 0.2805 | 0.1502 | 0.1544 | 0.1545 |

Table B.18: Heterogeneous Effects for High Tech Industry

**Notes:** *High-tech* is a dummy variable equal to 1 for ISIC 3.1 industry codes 24, 29, 30, 31, 32, 33, 34, 352, 353, 359, 2423, based on the technology intensity definition published by the OECD. Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .020 | | | .209** | | |
| | (.022) | | | (.089) | | |
| Workers Downstream Manufacturing* Sending | | .009 | | | .169* | |
| | | (.016) | | | (.094) | |
| Workers Same Industry * Sending | | | .017 | | | .214* |
| | | | (.024) | | | (.119) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 3,172 | 3,332 | 3,332 | 2,593 | 2,694 | 2,694 |
| R-Squared | 0.2174 | 0.2343 | 0.2343 | 0.2607 | 0.1544 | 0.2623 |

Table B.19: Exports - Foreign Owned Firms

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

| | Probability of Exporting | | | Export Value | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | .054** | | | .106 | | |
| | (.025) | | | (.110) | | |
| Workers Downstream Manufacturing* Sending | | .126** | | | .343 | |
| | | (.055) | | | (.024) | |
| Workers Same Industry * Sending | | | .021 | | | .340** |
| | | | (.029) | | | (.136) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| Controls×Industry FE | Y | Y | Y | Y | Y | Y |
| N of observations | 8,876 | 9,113 | 9,113 | 5,113 | 5,209 | 5,209 |
| R-Squared | 0.2104 | 0.1605 | 0.2322 | 0.1887 | 0.1605 | 0.1611 |

Table B.20: High Medium Technology Industries Only

**Notes:** Note that in this case we have considered all firms (foreign owned and domestically owned) in order to keep the sample size large. Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The coefficients of the variables defined as *network* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

## B.4 Figures

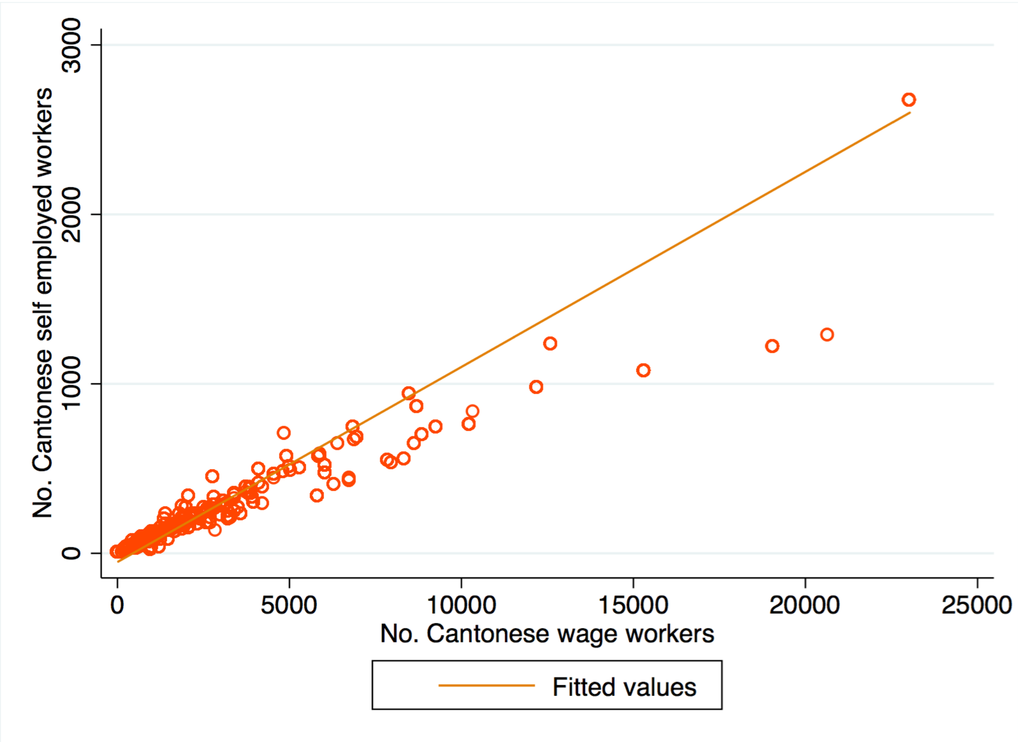


Figure B.1: Correlation between Workers and Self-employed Workers - Downstream Manufacturing

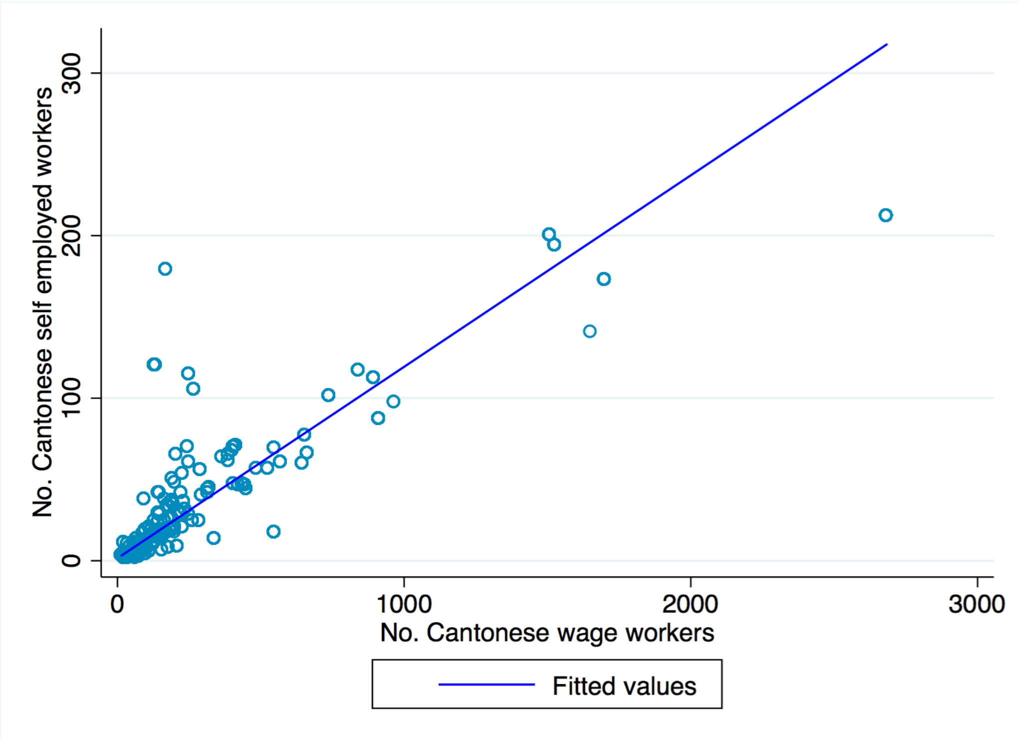


Figure B.2: Correlation between Workers and Self-employed Workers - Related Retail

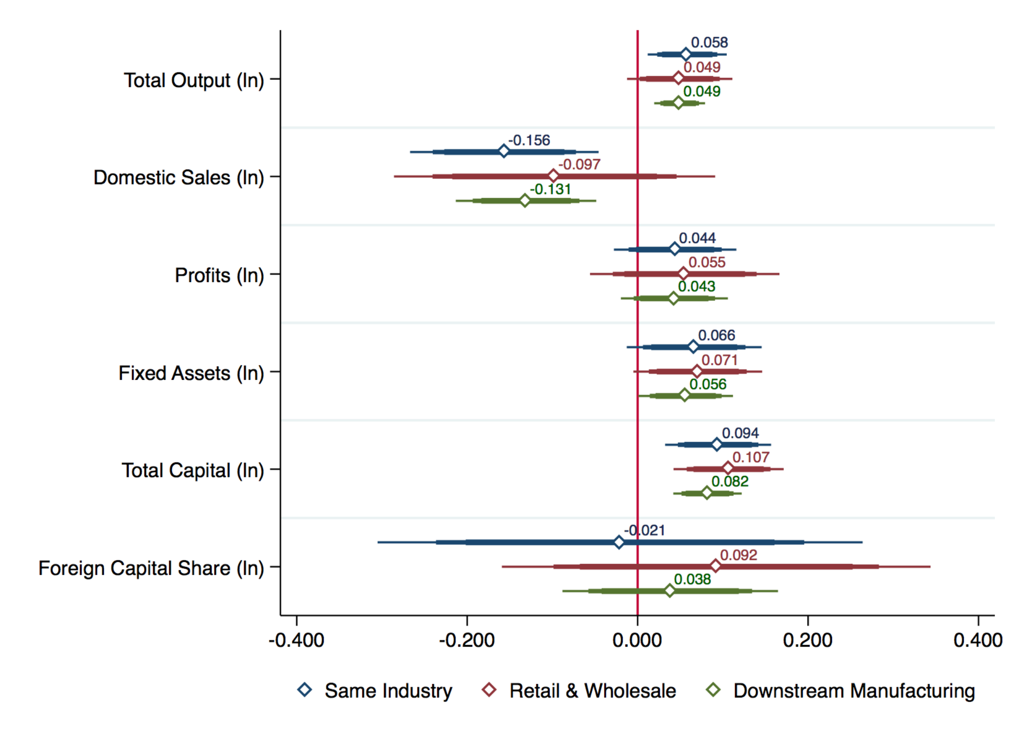


Figure B.3: Firm Outcomes: Output, Assets and Capital

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. This graph plots the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The confidence intervals given are at the 99%, 95% and 90% level.

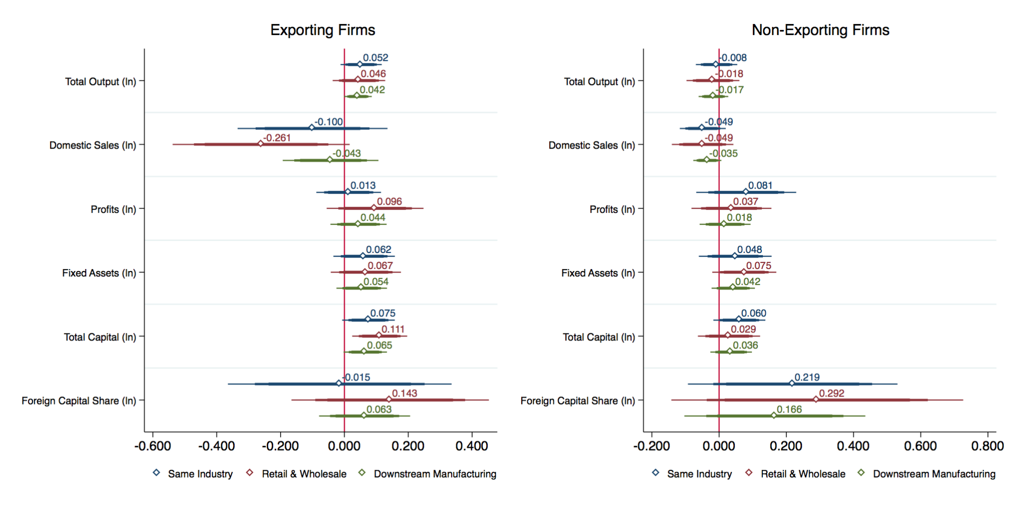


Figure B.4: Firm Outcomes: Output, Assets and Capital by Export Status

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. These graphs plot the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The confidence intervals given are at the 99%, 95% and 90% level.

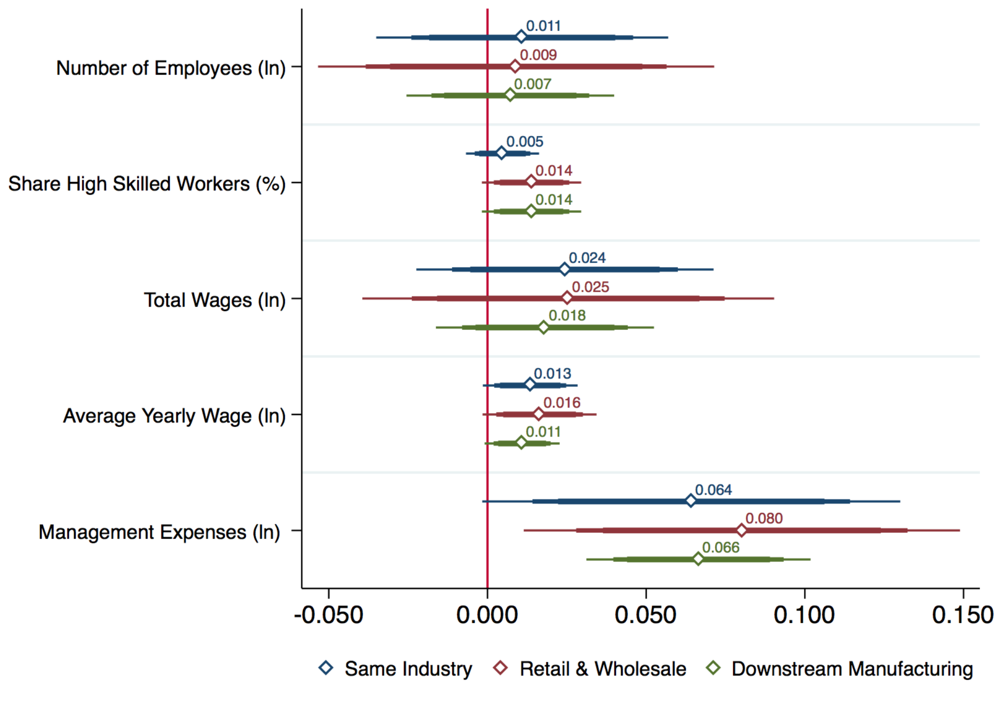


Figure B.5: Firm Outcomes: Employment and Expenses

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. This graph plots the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The variable *average yearly wage* indicates the yearly average wage paid per worker. The confidence intervals given are at the 99%, 95% and 90% level.


Figure B.6: Firm Outcomes: Employment and Expenses by Export Status

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. These graphs plot the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The variable *average yearly wage* indicates the yearly average wage paid per worker. The confidence intervals given are at the 99%, 95% and 90% level.

## B.5 Economic Census Data

In addition to analysing the effect on other firm variables for large manufacturing firms, we analyse data from the Economic Census of China to document the effects on small firms and firms in other sectors.

The Chinese Economic Census of 2004 is also compiled by the National Bureau of Statistics of the PRC and was accessed through the China Data Center at the University of Michigan. It contains information on the universe of all registered Chinese firms and thus contains a large number of observations. In contrast to the Survey of Industrial Enterprises, the census covers all industries and thus allows us to analyse also effects on services. Note that this data set nests the previous one. However, it contains only few firm-level variables, namely: employee number, revenues, 4 digit industry classification, ownership type and exact location. For privacy reasons, employee number and revenues are only given in bandwidths. We aggregate the location up to the county level to match it with our independent variable measuring network exposure. Again, we exclude all state-owned firms. This gives us 243,205 firm-level observations, out of which around 15% are at least partially foreign owned. As Figure 3.2 shows the distribution of firms according to ownership. As can be seen, most foreign owned firms are owned by individual or corporations based in Hong Kong, Macao or Taiwan. Table B.21 show the summary statistics for this data set.

| | Mean | Median | SD | Min | Max | N |
|---|---|---|---|---|---|---|
| | | | **Firm Level Statistics** | | | |
| Employee Number | 275.4835 | 10 | 3153.054 | 10 | 50000 | 243205 |
| Revenue | 1393.8407 | 75 | 8194.665 | 15 | 200000 | 243205 |
| | | | **County Level Statistics** | | | |
| Number of Firms | 13.55497 | 3 | 47.00418 | 1 | 2440 | 17945 |
| % Firms $<$ 10 Workers | 57.38828 | 66.66667 | 40.94633 | 0 | 100 | 17945 |
| % Firms $>$ 10, $<$ 250 Workers | 28.86719 | 11.20332 | 35.32179 | 0 | 100 | 17945 |
| % Firms $>$ 250 Workers | 13.74453 | 0 | 27.65033 | 0 | 100 | 17945 |

Table B.21: Descriptive Statistics: Chinese Economic Census

**Notes:** This table shows the descriptive statistics of the main variables used in this paper. Data from the Chinese Economic Census of 2004.

Table B.22 shows the effect on the log number of employees by sector. Note that while we can construct a measure of network exposure within the same industry for all industries in our sample, we are only able to calculate the number of workers in related retail and downstream manufacturing industries for manufacturing plants, as the other industries do not produce tradable goods. Column (1) shows that a one standard deviation increase in exposure to the network in the same industry increases employment for all firms by 2.7%. Column (4), (5) and (6) display the effect for manufacturing, services and retail firms respectively. The effect is significant only for the manufacturing sector, in which it is an around 7.5% increase. Column (2) and (3) show that our other measures of network have a similar effect on manufacturing firms. Figure B.7 delves deeper into the effect of network exposure on the size distribution of firms, and shows that the main increase in average size appears to be driven by a decrease in the share of firms with less than 20 workers and an increase in the share of firms that have between 20-50 workers.

Furthermore, the effects on revenues per worker are shown in Table B.23. Here, we find no effect of an increased exposure to the retail and downstream manufacturing industry network. We do however observe a negative overall effect of increased access to the network in the same industry in the US, and column (4) shows a positive effect for manufacturing firms: a one standard deviation increase in the measure of exposure increases revenue per worker by 3.5%. However, this effect is evened out by the negative effect on firms in the retail sector, as is shown in column (6).

| | Log Number of Employees | | | | | |
|---|---|---|---|---|---|---|
| | All Firms | Manufacturing | | | Services | Retail |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Workers Retail* Sending | | .069* | | | | |
| | | (.038) | | | | |
| Workers Same Workers Downstream Manufacturing * Sending | | | .094*** | | | |
| | | | (.015) | | | |
| Workers Same Industry * Sending | .027*** | | | .075** | .004 | .002 |
| | (.007) | | | (.036) | (.018) | (.004) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 234,542 | 108,304 | 146,724 | 109,755 | 30,205 | 94,394 |
| R-Squared | 0.3389 | 0.2155 | 0.2853 | 0.2147 | 0.1032 | 0.1187 |

Table B.22: Log Employment by Sectors - Economic Census Data

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The variables denoted as *workers* refers to the number of Cantonese workers in each 4-digit industries in the U.S. The coefficients of the variables *network* and *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

Figure B.8 shows the effect of all three measures on manufacturing firms of different sizes. While exposure to the same industry network increases the revenue per worker for small and medium sized manufacturing firms, exposure to the network in retail and wholesale industries has no significant effects, and in the case of downstream manufacturing, there is only a significant positive effect for firms employing between 50 and 500 workers. While there seems no significant effect for large firms, it is important to keep in mind that the bandwidths in which revenues and employment are noted become less precise at higher levels.

| | Log Revenue per Workers | | | | | |
|---|---|---|---|---|---|---|
| | All Firms | Manufacturing | | | Services | Retail |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Network Related Retail | | .018 | | | | |
| | | (.020) | | | | |
| Workers Downstream Manufacturing * Sending | | | .016 | | | |
| | | | (.013) | | | |
| Workers Same Industry * Sending | -.030** | | | .035** | .005 | -.029* |
| | (.013) | | | ( .014) | (.015) | (.016) |
| Age | Y | Y | Y | Y | Y | Y |
| Industry FE | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| N of observations | 234,542 | 109,755 | 109,755 | 109,755 | 30,205 | 94,394 |
| R-Squared | 0.3389 | 0.2155 | 0.2853 | 0.2147 | 0.1032 | 0.1187 |

Table B.23: Log Revenue per Worker by Sectors - Economic Census Data

**Notes:** Standard errors in parenthesis and clustered at the four-digit Chinese industry level. The variables denoted as *workers* refers to the number of Cantonese workers in each 4-digit industries in the U.S. The coefficients of the variables *network* and *workers* correspond to the changes in the dependent variable caused by a 1 SD change in the independent variable. ***p>0.01 **p>0.05 *p>0.10

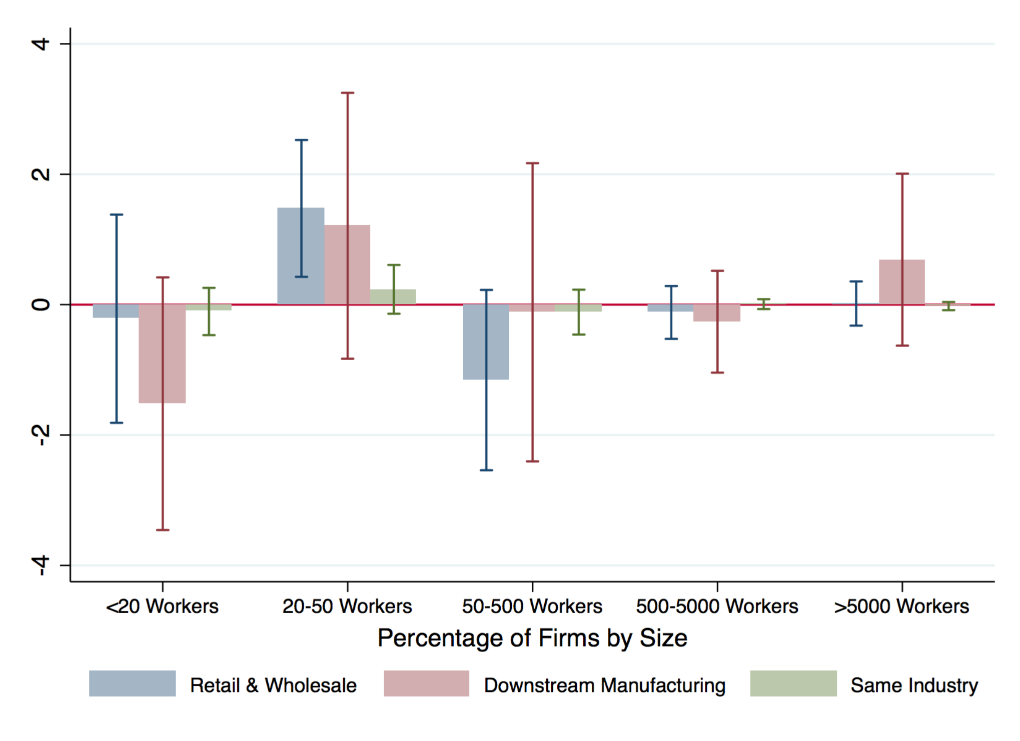


Figure B.7: Economic Census: Effect on Size Distribution - Manufacturing

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. This graph plots the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The confidence intervals given are at 90% level.

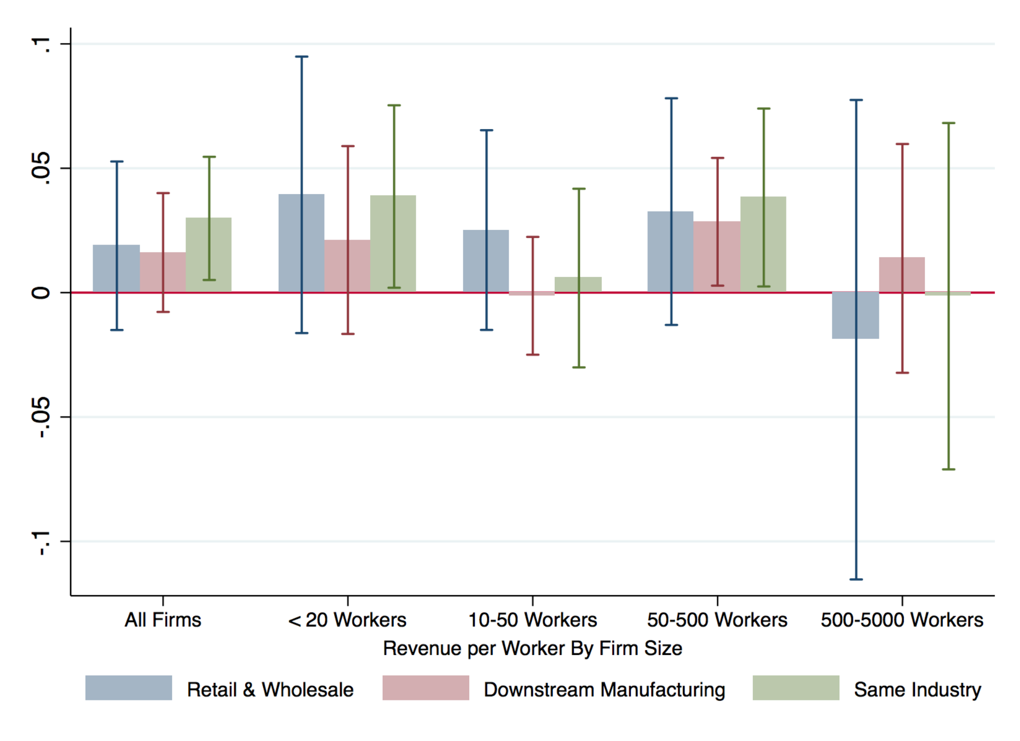


Figure B.8: Economic Census: Effect on Revenue per Worker by Firm Size - Manufacturing

**Notes:** Standard errors are clustered at the four-digit Chinese industry level. This graph plots the coefficients of the variable *network exposure* estimated in equation (4) for the three different measures of industry exposure; the coefficients correspond to the effect of a 1 SD change in the measure of network exposure. The confidence intervals given are at 90% level.

# Appendix C

# Product Customisation and Optimal Firm Size

## C.1 Proof

The proof follows through backward induction.

### C.1.1 Stage 4: Customised Firm's Pricing Decision

The set of players is the set of standardised firms $N^s$ and customised firms $N^c = M$. Each firm $i \in N^c$ maximises its profit. Firm types (s,c) are common knowledge at the beginning of the pricing stage.

At this stage all players have complete information. As standardised firms can choose a different price for each local market, and customised firms only operate in one market, I can analyse the problem for each market separately. I focus on a given market in the post-entry subgames. However, a similar game is played in each market. Thus, I drop the subscript indicating the local market in the following two sections unless required for clarity.

In this stage, the customised firm chooses the set of profit maximising prices as a function of the number of standardised firms shipping to the local market , $N^s$, their location in the product space $\mathbf{a}(a_1, ...a_{N^s})$, their cost parameter $\mathbf{k}(k_1, ...k_{N^s})$ and their prices $\mathbf{p}(p_1, ...p_{N^s})$. Given this information, customised firms choose a continuum of prices, as they are able to choose a different price for each variety.

Let the set of consumers that purchase from the customised firm $j$ in a given market be denoted by $\varphi^c_{m,j}(p)$. The profit of customised firm $j$ in market $m$ is thus given by:

$$\Pi_j = \int_0^1 (p_{j,l} - \kappa) F_{j,l}(p)\, dl \quad \text{where} \quad F_{j,l}(p) = \begin{cases} 1 & \text{if } l \in \varphi^c_{m,j}(p) \\ 0 & \text{otherwise} \end{cases}$$

**Market Shares and Profits**

Suppose that at least one standardised firm ships to market m. Label the customised firm as $c$. Starting at a random point on the circle, label each standardised firm $i = \{1, ..., N\}$ such that firm i's neighbour in the clockwise direction is labeled as $i + 1$ and in the anti-clockwise direction as $i - 1$. As explained in the previous section, to make the analysis tractable, I consider only the case where no standardised firm is undercut by another standardised firm in each market it operates in, i.e. all standardised firms sell to a positive mass of consumers *conditional on shipping to a given market* unless they are undercut by the customised firm. I start by analysing which consumers located between firm i and i+1 choose to purchases from the customised firm and then aggregate this over all pairs of standardised neighbours in the market to obtain the total market share of the customised firm c.

Denote the location of firm $i$ and $i + 1$ by $a_i$ and $a_{i+1}$ respectively. First suppose that in the absence of a customised firm operating in the market, there existed a consumer $x_{i,i+1}$ located between $a_i$ and $a_{i+1}$ such that any consumer with a larger distance from firm i purchases from firm i+1, while any consumer with a distance smaller purchases from firm i. Call this consumer the *marginal consumer*. This marginal consumer is relevant for the analysis in this section to understand which firm the customised firm is competing with.

In this case, each consumer located between $a_i$ and $x_{i,i+1}$ will purchase from firm c if:

$$p_c(l)_{l \in [a_i, x_{i,i+1}]} \leq p_i + \theta |l - a_i|$$

Similarly, suppose that there is also a marginal consumer $x_{i-1,i}$ located between firm i and firm i-1. In this case, any consumer located between $x_{i-1,i}$ and $a_i$ will purchase from firm c if:

$$p_c(l)_{l\in[x_{i-1,i},a_i]} \leq p_i + \theta|l - a_i|$$

Note that as the customised firm can choose a different price for each variety, we cannot say more at this point about the set of consumers who purchase from the customised firm without restricting the set of prices. Note for example, that the customised firm does not necessarily sell to a compact set of consumers between firm i and i+1.

Profits of the customised firm in this case become:

$$\Pi_c = \sum_{i=1}^{N^s} \left\{ \int_{x_{i-1,i}}^{x_{i,i+1}} \Big(p_c(l) - \kappa\Big) \cdot F_{c,i}(l)\; dl \right\} \text{ where } F_{c,i}(l) = \begin{cases} 1 & \text{if } p_c(l) \leq p_i + \theta|l - a_i| \\ 0 & \text{otherwise} \end{cases}$$

Note that if no standardised firm ships to market, any consumer will purchase from firm c if $p_c(l) \leq v_m$

**Pricing**

Note that the customised firm can choose a different price for each variety and thus chooses an infinite number of prices. It can be shown that if at least one standardised firm is active in market m, the optimal pricing schedule of the customised firm as a function of the preferred variety of consumer $l$ follows the following proposition.

**Proposition 3** *The optimal pricing schedule of the customised firm for each variety $l \in [a_i, x_{i,i+1}]$ for any firm i and i+1 is given by:*

$$p_c(l) = max\left\{p_i + \theta|l - a_i|, \kappa\right\} \tag{C.1}$$

**Proof:** To show that this pricing schedule is optimal, suppose that $l \in [x_{i-1,i}, x_{i,i+1}]$ is such that $p_i\theta|l - a_i| > \kappa$ and therefore, according to the proposition above the customised firm sets $p_c(l) = p_i\theta|l - a_i|$. Given the tie-breaking rule that has been assumed, in this case, consumer $l$ purchases the good from firm c. Profits from this particular consumer $l$ are then given by $\pi_c(l) = p_i\theta|l - a_i| - \kappa$, which are by assumption greater or equal to zero. I show that there is no profitable deviation: If firm c raises the price for consumer l, the consumer would then switch to purchase from firm i, according to the preferences outlined. In this case, profits would be equal to zero. If on the hand, firm c lowers it's price, consumer $l$ continues to purchase from firm c, but profits are strictly decreased. Thus there is no profitable deviation for $l \in [x_{i-1,i}, x_{i,i+1}]$ if $p_i\theta|l - a_i| \geq \kappa$.

Now suppose that $p_i\theta|l - a_i| < \kappa$ and thus the customised firm c sets $p_c(l) = \kappa$ accordingly. In this case, the consumer will purchase from firm i, as $p_i\theta|l - a_i| < p_c(l)$. Thus $F_{c,i}(l) = 0$ and as a result profits of firm c are equal to zero. If firm c now raises its prices, the consumer will continue to purchase from firm i and profits remain at zero. If firm c, however, lowers $p_c(l)$, either profits remain equal to zero if $p_c(l) > p_i\theta|l - a_i|$,as the consumer again continues to purchase from firm i or if firm c lowers its prices such that $p_c(l) > p_i\theta|l - a_i|$ , the consumer switches to purchase from firm c. In this case, though, profits become negative as now prices are below marginal costs i.e. $p_c(l) \leq \kappa$. The same argument follows for consumers located between the marginal consumers of any firm $i \in N^s$. Thus, there exist no profitable deviation from the pricing schedule as outlined by Proposition 6.

If no standardised firm is active in market m, firm c sets its price equal to the reservation price of the consumer $p_c(l) = v_m$. Thus as a result, the market share of the customised firm is equal to one and profits are given by $Pi_{c,m} = v_m - \kappa$.

### C.1.2 Stage 3: Standardised Firm's Pricing Decision

In this stage, in each market all standardised firms active in the said market simultaneously choose their prices as a function of the varieties produced and their marginal costs. Each firm $i \in N^s$ maximises its profit. I solve this stage in three steps. First, I calculate market shares and profits in the case where no standardised firm is undercut by another standardised firm and the customised firm supplies to a non-zero mass of consumers between all standardised firms. In a second step, I then establish restrictions on marginal costs and locations such that previous assumptions hold in equilibrium. In the third step, I then calculate optimal prices.

### Market Shares and Profits without Undercutting

Suppose no standardised firm is undercut. As before, suppose that there existed a consumer $x_{i,i+1}$ located between $a_i$ and $a_{i+1}$ such that

$$p_i + \theta|x_{i,i+1} - a_i| = p_{i+1} + \theta|a_{i+1} - x_{i,i+1}|$$

As each standardised firm can choose a single price, the left hand side is strictly monotonically increasing in the distance from $a_i$, while the right hand side is strictly monotonically decreasing in the distance from $a_i$, such a consumer exists as long as $p_i \leq p_{i+1} + \theta|a_{i+1} - a_i|$. This implies that in the absence of the customised firm any consumer located between $a_i$ and $x_{i,i+1}$ purchases the variety provided by firm i. Solving for $x_{i,i+1}$ gives

$$x_{i,i+1} = \frac{a_{i+1} + a_i}{2} + \frac{p_{i+1} - p_i}{2\theta}$$

Further, suppose that there exists a consumer $x_{i,c}$ such that:

$$p_i + \theta|x_{i,c} - a_i| - \epsilon = p_c(x_{i,c})$$

Recall that the customised firm's optimal strategy is to set its price equal to the maximum of the standardised price plus the cost to the consumer of purchasing a variety different to its own or its marginal cost $\kappa$. Therefore, the above equation can only hold if $p_c(x_{i,c}) = \kappa$, i.e. the standardised firm anticipates that it will only be able outprice the customised firm for consumers that are located at a distance from firm i such that adjusted price of firm i is smaller or equal to the customised firms marginal cost. For any price $p_i + \theta|x_{i,c} - a_i| > \kappa$, the optimal strategy of the customised firm is to set $p_c(l) = p_i + t + \theta|x_{i,c} - a_i|$ and due to the tie-breaking rule, the consumer will purchase from the customised firm instead.

Therefore, $x_{i,c}$ is given by:

$$x_{i,c} = a_i + \frac{\kappa - p_i}{\theta} - \epsilon$$

As $\epsilon$ can be arbitrarily small, I dropped it for ease of presentation.

In the absence of the previous assumptions, the standardised firms market share would be given by the set of consumers that are located between $a_i$ and the closer of the two marginal consumers. Thus the location of if $|x_{i,c}$ and $|x_{i,i+1}$ allow us to distinguish who the standardised firm i is in competition with: if $|x_{i,c} - a_i| < |x_{i,i+1} - a_i|$ then the salient competitor of firm i is the customised firm, and if $|x_{i,c} - a_i| \geq |x_{i,i+1} - a_i|$ it is standardised firm i+1. In the latter case, the customised firm would serve no consumers between the locations $a_i$ and $a_{i+1}$. The same considerations hold for consumers located between firm i and firm i-1.

However, I restrict to cases where in equilibrium, the customised firm supplies to a positive mass of consumers located between each standardised firm i and i+1. This is the case, if we have $|x_{i,c}^{i+1} - a_i| < |x_{i,i+1} - a_i|$ and $|x_{i,c}^{i-1} - a_i| < |x_{i-1} - a_i|$. In this case, using the market shares calculated above, the expression for profits of the standardised firm becomes:

$$\Pi_{i,m} = \frac{2}{\theta} L(\kappa - p_i)(p_i - k_i - td_m) \tag{C.2}$$

Note how in this case, the profits of firm i are independent of the behaviour of its neighbours i+1 and i-1.

### Condition for No Undercutting

In this section, I define the restrictions such that no standardised firm is undercut by another standardised firm, nor a customised firm locally undercut in equilibrium. Recall that I defined a customised firm $c$ as *locally undercut* if it makes no sales in the set of of consumers $L_{i,i+1} \in [a_i, a_{i+1}]$ for all standardised firms $i = \{1, ...n\}$. I defined a standardised firm $i$ as being undercut in a given market if it makes no sales in equilibrium in that market.

**Proposition 4** *Suppose that locations and marginal costs are such that $k_i \leq k_j - \theta|a_i - a_j|$. In this case, no standardised firm is undercut. Moreover, if*

$\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{1}{2N_m^s}$ *, the customised firm is locally undercut for no standardised firms i and i+1.*

$\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{a_{i+1}-a_i}{2}$ **Proof:** Suppose standardised firm $i$ deviates and undercuts standardised firm $j$. This implies that firm i charges a price no greater than $\underline{p_i} + \theta|a_i - a_j| = k_j$. The only case in which this deviation would be profitable is if this price charged is larger $\underline{p_i} \geq k_i + td_m$. Thus no standardised firm undercuts another standardised firm if the distance between the varieties supplied by the two firms is large enough relative to the difference in productivity, i.e. have:

$$k_i \geq k_j - \theta|a_i - a_j|$$

Now, suppose standardised firm $i$ does not find it profitable to undercut either of its standardised neighbours [1], but instead deviates and locally undercuts the customised firm c between i and i+1. Firm i locally undercuts the customised firm if it charges a price such that for all consumers $l \in [a_i, x_{i,i+1}]$, $p_i + \theta|l - a_i| < \kappa$, which would lead all consumers located between $a_i$ and $a_{i+1}$ to buy either from standardised firm i or i+1. Note that profits of this deviation depend on the price charged by firm i+1 through the location of $x_{i,i+1}$. The upper bound on this price, however, is the highest, when the price charged by firm i+1 is the lowest, i.e. $p_{i+1} = k_i + td_m$. At the same time, it is also necessary to have $p_i \geq k_i + td_m$ for this to be a profitable deviation for firm i, which is the lowest if the distance of the given market to the central location is the smallest i.e. zero. Thus, no standardised firm i will find it profitable to locally undercut the customised firm if $k_i + td_m + \theta|x_{i,i+1} - a_i| < \kappa$, which then becomes:

$$\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{a_{i+1}-a_i}{2}$$

As the distance between any firm i and i+1 is equal to $\frac{1}{N_m^s}$, I make for all markets $m \in M$, the following assumption:

**Assumption 5** *Let locations and marginal costs be such that* $k_i \geq k_j - \theta|a_i - a_j|$ *and* $\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{1}{2N_m^s}$ *.*

[1]Note that undercutting a standardised neighbour i+1 automatically implies locally undercutting the customised firm between firm i and i+1

Note however, that I do not restrict that the standardised firm is being undercut by *the customised firm*. Due to the fact that the salient competitor for each standardised firm is the customised firm, allowing this does not complicate the analysis significantly. Note that the customised firm could find it profitable to undercut standardised firm i if the distance of the given market to the central location is large enough such that:

$$d_m \geq \frac{\kappa - k_i}{t}$$

**Pricing**

Given the restrictions imposed in the previous section, profits are continuous and convex. Thus, the optimal price is found through simple profit maximisation and are pinned-down by the following proposition:

**Proposition 5** *Given that no firm is undercut and the customised firm sells to a positive mass of consumers, standardised firm i's optimal price is given by:*

$$p_i^* = \frac{1}{2}(k_i + td_m + \kappa) \tag{C.3}$$

*As a result market shares are given by:*

$$x_i = \frac{\kappa - k_i - td_m}{\theta} \tag{C.4}$$

Note that in this case, the optimal price is given by an average of the firms own marginal cost and the marginal cost of the customised firm. Given the optimal price, profits are given by:

$$\Pi_{i,m} = \begin{cases} L\frac{1}{2\theta}\left[\kappa - k_i - td_m\right]^2 & \text{if } d_m \geq \frac{\kappa - k_i}{t} \\ 0 & \text{otherwise} \end{cases} \tag{C.5}$$

In this case profits and prices are independent of the distance between the standardised firms, and only depend on the marginal cost of the customised firm.

Given the above pricing strategy of the standardised firms, the market share of the customised firm is given by:

$$x_{c,m} = L \sum_{i=1}^{N^s} \frac{1}{\theta} \left[ \frac{k_i + k_{i+1}}{2} + td_m + \frac{\theta}{N_m^s} - \kappa \right] \tag{C.6}$$

which can be rewritten as:

$$x_{c,m} = max \left\{ 1 - \frac{N_m^s}{\theta} \left( \kappa - \bar{k}_m - td_m \right), 1 \right\} \tag{C.7}$$

where, $\bar{k}_m$ is the average marginal cost of the standardised firms that is active in market m. Profits of the customised firm are then given by the integral

$$\Pi_{c,m} = L \sum_{i=1}^{N^s} \int_{a_i}^{x_{i,i+1}} \left( \frac{1}{2}(k_i + td_m - \kappa) + \theta |l - a_i| \right) dl + \int_{x_{i,i+1}}^{a_{i+1}} \left( \frac{1}{2}(k_i + 1 + td_m - \kappa) + \theta |l - a_i| \right) dl$$

which simplifies to:

$$\Pi_{c,m} = L \sum_{i=1}^{N^s} \frac{1}{2\theta} \left[ \frac{k_i + k_{i+1}}{2} + td_m + \frac{\theta}{N_m^s} - \kappa \right]^2 \tag{C.8}$$

as the distance between the varieties produced by any firm i and i+1 is assumed to be $\frac{1}{N_m^s}$. Thus, the customised firms profits depend positively on the marginal cost of the standardised firms i and i+1 as well as on the distance between firm i and i+1's location.

## C.2 Proof

The proof follows through backward induction.

### C.2.1 Stage 4: Customised Firm's Pricing Decision

The set of players is the set of standardised firms $N^s$ and customised firms $N^c = M$. Each firm $i \in N^c$ maximises its profit. Firm types (s,c) are common knowledge at the beginning of the pricing stage.

At this stage all players have complete information. As standardised firms can choose a different price for each local market, and customised firms only operate in one market, I can analyse the problem for each market separately. I focus on a given market in the post-entry subgames. However, a similar game is played in each market. Thus, I drop the subscript indicating the local market in the following two sections unless required for clarity.

In this stage, the customised firm chooses the set of profit maximising prices as a function of the number of standardised firms shipping to the local market , $N^s$, their location in the product space $\mathbf{a}(a_1, ...a_{N^s})$, their cost parameter $\mathbf{k}(k_1, ...k_{N^s})$ and their prices $\mathbf{p}(p_1, ...p_{N^s})$. Given this information, customised firms choose a continuum of prices, as they are able to choose a different price for each variety.

Let the set of consumers that purchase from the customised firm $j$ in a given market be denoted by $\varphi^c_{m,j}(p)$. The profit of customised firm $j$ in market $m$ is thus given by:

$$\Pi_j = \int_0^1 (p_{j,l} - \kappa)F_{j,l}(p)\, dl \quad \text{where} \quad F_{j,l}(p) = \begin{cases} 1 & \text{if } l \in \varphi^c_{m,j}(p) \\ 0 & \text{otherwise} \end{cases}$$

### Market Shares and Profits

Suppose that at least one standardised firm ships to market m. Label the customised firm as $c$. Starting at a random point on the circle, label each standardised firm $i = \{1, ..., N\}$ such that firm i's neighbour in the clockwise direction is labeled as $i + 1$ and in the anti-clockwise direction as $i - 1$. As explained in the previous section, to make the analysis tractable, I consider only the case where no standardised firm is undercut by another standardised firm in each market it operates in, i.e. all standardised firms sell to a positive mass of consumers *conditional on shipping to a given market* unless they are undercut by the customised firm. I start by analysing which consumers located between firm i and i+1 choose to purchases from the customised firm and then aggregate this over all pairs of standardised neighbours in the market to obtain the total market share of the customised firm c.

Denote the location of firm $i$ and $i + 1$ by $a_i$ and $a_{i+1}$ respectively.

First suppose that in the absence of a customised firm operating in the market, there existed a consumer $x_{i,i+1}$ located between $a_i$ and $a_{i+1}$ such that any consumer with a larger distance from firm i purchases from firm i+1, while any consumer with a distance smaller purchases from firm i. Call this consumer the *marginal consumer*. This marginal consumer is relevant for the analysis in this section to understand which firm the customised firm is competing with.

In this case, each consumer located between $a_i$ and $x_{i,i+1}$ will purchase from firm c if:

$$p_c(l)_{l\in[a_i,x_{i,i+1}]} \leq p_i + \theta|l - a_i|$$

Similarly, suppose that there is also a marginal consumer $x_{i-1,i}$ located between firm i and firm i-1. In this case, any consumer located between $x_{i-1,i}$ and $a_i$ will purchase from firm c if:

$$p_c(l)_{l\in[x_{i-1,i},a_i]} \leq p_i + \theta|l - a_i|$$

Note that as the customised firm can choose a different price for each variety, we cannot say more at this point about the set of consumers who purchase from the customised firm without restricting the set of prices. Note for example, that the customised firm does not necessarily sell to a compact set of consumers between firm i and i+1.

Profits of the customised firm in this case become:

$$\Pi_c = \sum_{i=1}^{N^s} \left\{ \int\limits_{x_{i-1,i}}^{x_{i,i+1}} \Big(p_c(l) - \kappa\Big) \cdot F_{c,i}(l)\, dl \right\} \text{ where } F_{c,i}(l) = \begin{cases} 1 & \text{if } p_c(l) \leq p_i + \theta|l - a_i| \\ 0 & \text{otherwise} \end{cases}$$

Note that if no standardised firm ships to market, any consumer will purchase from firm c if $p_c(l) \leq v_m$

**Pricing**

Note that the customised firm can choose a different price for each variety and thus chooses an infinite number of prices. It can be shown that if at least one standardised firm is active in market m, the optimal pricing schedule of the customised firm as a function of the preferred variety of consumer $l$ follows the following proposition.

**Proposition 6** *The optimal pricing schedule of the customised firm for each variety $l \in [a_i, x_{i,i+1}]$ for any firm i and i+1 is given by:*

$$p_c(l) = max\{p_i + \theta|l - a_i|, \kappa\} \tag{C.9}$$

**Proof:** To show that this pricing schedule is optimal, suppose that $l \in [x_{i-1,i}, x_{i,i+1}]$ is such that $p_i\theta|l - a_i| > \kappa$ and therefore, according to the proposition above the customised firm sets $p_c(l) = p_i\theta|l - a_i|$. Given the tie-breaking rule that has been assumed, in this case, consumer $l$ purchases the good from firm c. Profits from this particular consumer $l$ are then given by $\pi_c(l) = p_i\theta|l - a_i| - \kappa$, which are by assumption greater or equal to zero. I show that there is no profitable deviation: If firm c raises the price for consumer l, the consumer would then switch to purchase from firm i, according to the preferences outlined. In this case, profits would be equal to zero. If on the hand, firm c lowers it's price, consumer $l$ continues to purchase from firm c, but profits are strictly decreased. Thus there is no profitable deviation for $l \in [x_{i-1,i}, x_{i,i+1}]$ if $p_i\theta|l - a_i| \geq \kappa$.

Now suppose that $p_i\theta|l - a_i| < \kappa$ and thus the customised firm c sets $p_c(l) = \kappa$ accordingly. In this case, the consumer will purchase from firm i, as $p_i\theta|l - a_i| < p_c(l)$. Thus $F_{c,i}(l) = 0$ and as a result profits of firm c are equal to zero. If firm c now raises its prices, the consumer will continue to purchase from firm i and profits remain at zero. If firm c, however, lowers $p_c(l)$, either profits remain equal to zero if $p_c(l) > p_i\theta|l - a_i|$,as the consumer again continues to purchase from firm i or if firm c lowers its prices such that $p_c(l) > p_i\theta|l - a_i|$ , the consumer switches to purchase from firm c. In this case, though, profits become negative as now prices are below marginal costs i.e. $p_c(l) \leq \kappa$. The same argument follows for consumers located between the marginal consumers of any firm $i \in N^s$. Thus, there exist no profitable deviation from the pricing schedule as outlined by Proposition 6.

If no standardised firm is active in market m, firm c sets its price equal to the reservation price of the consumer $p_c(l) = v_m$. Thus as a result, the market share of the customised firm is equal to one and profits are given by $Pi_{c,m} = v_m - \kappa$.

### C.2.2 Stage 3: Standardised Firm's Pricing Decision

In this stage, in each market all standardised firms active in the said market simultaneously choose their prices as a function of the varieties produced and their marginal costs. Each firm $i \in N^s$ maximises its profit. I solve this stage in three steps. First, I calculate market shares and profits in the case where no standardised firm is undercut by another standardised firm and the customised firm supplies to a non-zero mass of consumers between all standardised firms. In a second step, I then establish restrictions on marginal costs and locations such that previous assumptions hold in equilibrium. In the third step, I then calculate optimal prices.

#### Market Shares and Profits without Undercutting

Suppose no standardised firm is undercut. As before, suppose that there existed a consumer $x_{i,i+1}$ located between $a_i$ and $a_{i+1}$ such that

$$p_i + \theta|x_{i,i+1} - a_i| = p_{i+1} + \theta|a_{i+1} - x_{i,i+1}|$$

As each standardised firm can choose a single price, the left hand side is strictly monotonically increasing in the distance from $a_i$, while the right hand side is strictly monotonically decreasing in the distance from $a_i$, such a consumer exists as long as $p_i \leq p_{i+1} + \theta|a_{i+1} - a_i|$. This implies that in the absence of the customised firm any consumer located between $a_i$ and $x_{i,i+1}$ purchases the variety provided by firm i. Solving for $x_{i,i+1}$ gives

$$x_{i,i+1} = \frac{a_{i+1} + a_i}{2} + \frac{p_{i+1} - p_i}{2\theta}$$

Further, suppose that there exists a consumer $x_{i,c}$ such that:

$$p_i + \theta|x_{i,c} - a_i| - \epsilon = p_c(x_{i,c})$$

Recall that the customised firm's optimal strategy is to set its price equal to the maximum of the standardised price plus the cost to the consumer of purchasing a variety different to its own or its marginal cost $\kappa$. Therefore, the above equation can only hold if $p_c(x_{i,c}) = \kappa$, i.e. the standardised firm anticipates that it will only be able outprice the customised firm for consumers that are located at a distance from firm i such that adjusted price of firm i is smaller or equal to the customised firms marginal cost. For any price $p_i + \theta|x_{i,c} - a_i| > \kappa$, the optimal strategy of the customised firm is to set $p_c(l) = p_i + t + \theta|x_{i,c} - a_i|$ and due to the tie-breaking rule, the consumer will purchase from the customised firm instead.

Therefore, $x_{i,c}$ is given by:

$$x_{i,c} = a_i + \frac{\kappa - p_i}{\theta} - \epsilon$$

As $\epsilon$ can be arbitrarily small, I dropped it for ease of presentation.

In the absence of the previous assumptions, the standardised firms market share would be given by the set of consumers that are located between $a_i$ and the closer of the two marginal consumers. Thus the location of if $|x_{i,c}$ and $|x_{i,i+1}$ allow us to distinguish who the standardised firm i is in competition with: if $|x_{i,c} - a_i| < |x_{i,i+1} - a_i|$ then the salient competitor of firm i is the customised firm, and if $|x_{i,c} - a_i| \geq |x_{i,i+1} - a_i|$ it is standardised firm i+1. In the latter case, the customised firm would serve no consumers between the locations $a_i$ and $a_{i+1}$. The same considerations hold for consumers located between firm i and firm i-1.

However, I restrict to cases where in equilibrium, the customised firm supplies to a positive mass of consumers located between each standardised firm i and i+1. This is the case, if we have $|x_{i,c}^{i+1} - a_i| < |x_{i,i+1} - a_i|$ and $|x_{i,c}^{i-1} - a_i| < |x_{i-1} - a_i|$. In this case, using the market shares calculated above, the expression for profits of the standardised firm becomes:

$$\Pi_{i,m} = \frac{2}{\theta}L(\kappa - p_i)(p_i - k_i - td_m) \tag{C.10}$$

Note how in this case, the profits of firm i are independent of the behaviour of its neighbours i+1 and i-1.

**Condition for No Undercutting**

In this section, I define the restrictions such that no standardised firm is undercut by another standardised firm, nor a customised firm locally undercut in equilibrium. Recall that I defined a customised firm $c$ as *locally undercut* if it makes no sales in the set of of consumers $L_{i,i+1} \in [a_i, a_{i+1}]$ for all standardised firms $i = \{1, ...n\}$. I defined a standardised firm $i$ as being undercut in a given market if it makes no sales in equilibrium in that market.

**Proposition 7** *Suppose that locations and marginal costs are such that* $k_i \leq k_j - \theta|a_i - a_j|$. *In this case, no standardised firm is undercut. Moreover, if* $\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{1}{2N_m^s}$ *, the customised firm is locally undercut for no standardised firms i and i+1.*

$\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{a_{i+1}-a_i}{2}$ **Proof:** Suppose standardised firm $i$ deviates and undercuts standardised firm $j$. This implies that firm i charges a price no greater than $\underline{p_i} + \theta|a_i - a_j| = k_j$. The only case in which this deviation would be profitable is if this price charged is larger $\underline{p_i} \geq k_i + td_m$. Thus no standardised firm undercuts another standardised firm if the distance between the varieties supplied by the two firms is large enough relative to the difference in productivity, i.e. have:

$$k_i \geq k_j - \theta|a_i - a_j|$$

Now, suppose standardised firm $i$ does not find it profitable to undercut either of its standardised neighbours [2], but instead deviates and locally undercuts the customised firm c between i and i+1. Firm i locally undercuts the customised firm if it charges a price such that for all consumers $l \in [a_i, x_{i,i+1}]$, $p_i + \theta|l - a_i| < \kappa$, which would lead all consumers located between $a_i$ and $a_{i+1}$ to buy either from standardised firm i or i+1. Note that profits of this deviation depend on the price charged by firm i+1 through the location of $x_{i,i+1}$. The upper bound on this price, however, is the highest, when the price charged by firm i+1 is the lowest, i.e. $p_{i+1} = k_i + td_m$. At the same time, it is also necessary to have $p_i \geq k_i + td_m$ for this to be a profitable deviation for firm i, which

[2]Note that undercutting a standardised neighbour i+1 automatically implies locally undercutting the customised firm between firm i and i+1

is the lowest if the distance of the given market to the central location is the smallest i.e. zero. Thus, no standardised firm i will find it profitable to locally undercut the customised firm if $k_i + td_m + \theta|x_{i,i+1} - a_i| < \kappa$, which then becomes:

$$\kappa < \frac{k_{i+1} + k_i}{2} + \theta\frac{a_{i+1} - a_i}{2}$$

As the distance between any firm i and i+1 is equal to $\frac{1}{N_m^s}$, I make for all markets $m \in M$, the following assumption:

**Assumption 6** *Let locations and marginal costs be such that* $k_i \geq k_j - \theta|a_i - a_j|$ *and* $\kappa < \frac{k_{i+1}+k_i}{2} + \theta\frac{1}{2N_m^s}$ .

Note however, that I do not restrict that the standardised firm is being undercut by *the customised firm*. Due to the fact that the salient competitor for each standardised firm is the customised firm, allowing this does not complicate the analysis significantly. Note that the customised firm could find it profitable to undercut standardised firm i if the distance of the given market to the central location is large enough such that:

$$d_m \geq \frac{\kappa - k_i}{t}$$

**Pricing**

Given the restrictions imposed in the previous section, profits are continuous and convex. Thus, the optimal price is found through simple profit maximisation and are pinned-down by the following proposition:

**Proposition 8** *Given that no firm is undercut and the customised firm sells to a positive mass of consumers, standardised firm i's optimal price is given by:*

$$p_i^* = \frac{1}{2}(k_i + td_m + \kappa) \tag{C.11}$$

*As a result market shares are given by:*

$$x_i = \frac{\kappa - k_i - td_m}{\theta} \tag{C.12}$$

Note that in this case, the optimal price is given by an average of the firms own marginal cost and the marginal cost of the customised firm. Given the optimal price, profits are given by:

$$\Pi_{i,m} = \begin{cases} L\frac{1}{2\theta}\left[\kappa - k_i - td_m\right]^2 & \text{if } d_m \geq \frac{\kappa - k_i}{t} \\ 0 & \text{otherwise} \end{cases} \tag{C.13}$$

In this case profits and prices are independent of the distance between the standardised firms, and only depend on the marginal cost of the customised firm.

Given the above pricing strategy of the standardised firms, the market share of the customised firm is given by:

$$x_{c,m} = L\sum_{i=1}^{N^s}\frac{1}{\theta}\left[\frac{k_i + k_{i+1}}{2} + td_m + \frac{\theta}{N_m^s} - \kappa\right] \tag{C.14}$$

which can be rewritten as:

$$x_{c,m} = max\left\{1 - \frac{N_m^s}{\theta}\left(\kappa - \bar{k}_m - td_m\right), 1\right\} \tag{C.15}$$

where, $\bar{k}_m$ is the average marginal cost of the standardised firms that is active in market m. Profits of the customised firm are then given by the integral

$$\Pi_{c,m} = L\sum_{i=1}^{N^s}\int_{a_i}^{x_{i,i+1}}\left(\tfrac{1}{2}(k_i + td_m - \kappa) + \theta|l - a_i|\right)dl + \int_{x_{i,i+1}}^{a_{i+1}}\left(\tfrac{1}{2}(k_i + 1 + td_m - \kappa) + \theta|l - a_i|\right)dl$$

which simplifies to:

$$\Pi_{c,m} = L\sum_{i=1}^{N^s}\frac{1}{2\theta}\left[\frac{k_i + k_{i+1}}{2} + td_m + \frac{\theta}{N_m^s} - \kappa\right]^2 \tag{C.16}$$

as the distance between the varieties produced by any firm i and i+1 is assumed to be $\frac{1}{N_m^s}$. Thus, the customised firms profits depend positively on the marginal cost of the standardised firms i and i+1 as well as on the distance between firm i and i+1's location.

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