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Determinants of initial technology adoption and intensification: evidence from Latin America and the Caribbean

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ABSTRACT

In this paper we examine determinants of initial adoption and subsequent intensification of commercial use of the internet. In contrast to previous examinations that have looked at initial adoption and intensification in the highest income countries, we study companies in Latin America and the Caribbean and so contribute to empirical understanding of the two types of adoption. Many variables such as company size and industry intensification previously identified as influential in high income regions continue to be important determinants. Novel determinants are also found, including informal sector competition and regional influence. There are sharp differences in determinants between the two adoption types.

Keywords:

Technology, internet, adoption, intensification, developing countries

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1. Introduction

The identification of policies to promote technology diffusion to companies in developing countries has attracted the attention of policymakers and their advisors for decades. Sibanda (2015) argues that diffusion in Africa is supported by human capital development, a balanced intellectual property system, and research networks, while UNIDO (2015) suggests that technical assistance and financial support have encouraged the adoption of environmentally friendly manufacturing technologies in developing economies from the 1990s onwards. In the 1970s, ADL (1978) argued that the US government could most effectively support diffusion in Latin America by providing information to businesses on technologies, economic conditions, and market opportunities.

These proposals often aim at supporting comprehensive economic transformation in developing countries, or promoting green technologies in preference to polluting technologies. In the distinction emphasised by Battisti and Stoneman (2003), the proposals aim to increase both the initial adoption of technologies and the intensity of their use. Initial technology adoption is the first adoption of a technology by an agent, while intensification of use describes the subsequent extent of technology adoption by the agent. Initial adoption has been subject to many theoretical and empirical studies (Geroski 2000; Meade and Islam 2006), establishing regularities such as the existence of an S-shaped diffusion curve for individual technologies. Intensification has had far fewer studies, although following Battisti and Stoneman's (2003) comparative study of intensive and extensive use of technology, there has been a recent increase in the number of empirical studies of it (Battisti et al. 2007; Fuentelsaz, Gomez, and Polo 2003; Hollenstein and Woerter 2008).

The interpretations and policy recommendations given to date on intensification are most relevant to highly developed countries, as the prior empirical literature has focussed on data from these states. For example, Antonelli (1985) uses data from US and Western European companies, Battisti et al. (2007) work with British and Swiss data, Battisti and Iona (2009) employ UK data, Bocquet and Brossard (2007) use French data, Fuentelsaz, Gomez, and Polo (2003) have Spanish data, and in Hollenstein and Woerter (2008) Swiss data is used. As a result of the previous geographic focus in the literature, many interesting questions about intensification

relevant in lower income countries do not arise in the countries examined, and cannot be investigated with data from them. For example, frequent interruption of power supplies may differentially affect companies' choices of initial adoption and intensification in developing countries, but the consideration does not arise in high income countries where power supplies are guaranteed. Similarly, the informal economy is typically a larger proportion of the total economy in developing countries than in Western Europe and the United States, and formal sector companies may adjust their technological choices to reflect the competition.

In this paper we attempt to fill part of the gap by an empirical examination of determinants of initial technology adoption and intensification in regions other than the highest income countries previously examined in the literature. We address the following questions. Do the determinants of initial adoption and intensification already identified as applying in highest income countries also apply in poorer countries? What other determinants are significant in these poorer countries?

We examine initial adoption and subsequent intensification of commercial use of the internet by companies, working in the theoretical framework of Karshenas and Stoneman (1993) which divides influences on diffusion into rank, stock, order, and epidemic effects. The framework is applied to initial adoption and intensification in separate equations, as in Battisti et al. (2007) and Hollenstein and Woerter (2008). We keep determinant variables commonly recognised in the literature and introduce new rank and epidemic determinant variables that influence technology use in lower income countries particularly. The model is estimated using a dataset of companies from Latin America and the Caribbean in the year 2009-10.

We show that commonly included variables from the prior literature on the two types of diffusion in high income countries continue to have validity in lower income regions. These variables are company size, membership of a larger firm, experience with a precursor technology, and industry experience with the technology. We further show the influence of national development, through the role of newly introduced rank variables measuring financial obstacles, competition against informal companies, and presence in a capital city. A novel epidemic variable measuring regional use is also found to have significant effects. The determinants of initial adoption and

intensification are quite distinct. The former is affected by more variables, including national development variables, while the latter is influenced by industrial intensity of use, foreign ownership, and financial obstacles.

Section 2 gives our theoretical framework, section 3 describes our data, and section 4 presents our empirical method. Section 5 gives results, section 6 presents extensions to the basic results, and section 7 concludes.

2. Theoretical framework

Our theoretical framework is derived from a classification of influences on diffusion given in Karshenas and Stoneman (1993). The approach identifies rank, stock, order, and epidemic effects as possible influences on inter-firm diffusion. It was used in an empirical analysis of intra-firm diffusion in Battisti and Stoneman (2005), and then for larger inter- and intra-firm comparative investigations in Battisti, Canepa, and Stoneman (2009), Battisti et al. (2007), and Hollenstein and Woerter (2008), and with a variation to allow for technological fit in Bocquet and Brossard (2007).

In the formulation of Battisti, Canepa, and Stoneman (2009), the extent of use of a technology may be written as

$$x_i(t) = G(\tilde{F}_i(t), \tilde{F}_N(t), y_N(t), E_i(t), E_N(t), P_i(t)) \qquad (1)$$

where

$x_i(t)$ is the extent of use of technology by company *i* at time t,

G is a non-negative function,

$\tilde{F}_i(t)$ is a vector of company characteristics,

$\tilde{F}_N(t)$ is a vector of industry characteristics,

$y_N(t)$ is the extent of industry use of the technology,

$E_i(t)$ is a measure of the firm's own experience relevant to the technology,

$E_N(t)$ is a measure of the experience relevant to the technology that the firm gains from observing others, and

$P_i(t)$ is the expected adoption cost of a unit of the new technology.

$\tilde{F}_i(t)$ and $\tilde{F}_N(t)$ can be used to measure rank effects, which exist if different firm and industry characteristics affect the profitability and so level of adoption for individual companies. Certain rank effects, such as those due to power outages and competition against informal companies, primarily occur in developing countries or are much stronger there (Schneider and Enste 2000).

$y_N(t)$ is the extent of industry use of the technology and can be used to measure stock effects. A stock effect exists if the profitability of a company's use of a technology declines with the number of technology owners at the time the company uses the technology. Karshenas and Stoneman (1993) argue that as more companies adopt the technology, market prices for the end good decline thereby lowering the profitability of further adoption, so the stock effect changes after the date of adoption as the technology's use increases. The size of the stock effect can be measured by looking at how the cumulative number of adopters affects adoption probabilities.

An order effect exists if the profitability of a company's use of a technology declines with the number of owners of the technology at the time the company adopted the technology. The magnitude of the order effect is fixed at the date of adoption. Karshenas and Stoneman (1993) show that its impact can be measured by examining how the change in the cumulative number of adopters affects adoption probabilities. We do not have company time series so cannot use this measure, and we do not separately examine the order effect.

$E_i(t)$ and $E_N(t)$ can be used to measure internal and external epidemic effects. An epidemic effect exists if information diffusion from adopters increases a non-adopter's knowledge about the technology. The size of the epidemic effect may be assessed by looking at the impact of exposure to existing users of the technology or similar technology. An internal measure of such exposure may be the current extent of use within a company, while an external measure may be the extent of regional use of the technology. Information about use may move less freely in developing markets than in developed markets if lower rates of education limit people's ability to read and

understand communications about technologies (Rosenzweig 1995) for example, or if regional markets within countries are more isolated due to travel difficulties. Consequently, epidemic effects may have different strengths in developing and developed countries.

In our estimations we take two measures for $x_i(t)$, reflecting initial adoption and intensification of commercial use of the internet. To measure initial adoption by a company, we create a variable equal to one if a company has an internet connection, and zero otherwise. For intensification, we create a variable lying between zero and three, and equal to the number of the company's commercial practices that use the internet, from following list of distinct practices:

1. making purchases for the company,
2. delivering services to clients, and
3. doing research and developing ideas on new products and services.

For the rank variables, we consider commonly used variables, and variables describing the influences of ownership and national development. For stock and epidemic variables, the influences of internal, industrial, local, and international sources are considered. As in Battisti et al. (2007) and Hollenstein and Woerter (2008) we do not separate the negative impact of stock effects from the positive impact of epidemic effects, as they both act through the number of previous adopters in a cross-sectional analysis. Accordingly, we label the corresponding variables as epidemic effects and recognise that their coefficients describe net impacts, with a positive coefficient showing that epidemic effects are significantly stronger than stock effects, and a negative coefficient showing the opposite (in section 6 we change the epidemic variable definitions a little to see the impact of stock effects more clearly). Table 1 summarises the variables and their expected effects, which are described in more detail next.

[TABLE 1 ABOUT HERE]

Company size

We measure company size by two dummy variables, taking the values of one if the company has between 20 and 99 employees, and 100 or more employees. Small companies with fewer than 20 employees are left as a reference group. Different authors and governments use alternative categorisations of companies into these groups (Gibson and van der Vaart 2008). We retain the classification given by the data provider, the World Bank. As another categorisation, we tried dummies for companies with between 50 and 249 employees, and more than 250 employees. The size dummies lost their significance in the initial adoption, without altering our main results. When we inserted the number of employees directly into our equation, size regained its significance and confirmed the results using our initial dummies, so we have confidence that our categorisation accurately reflects the impact of size on technology use.

There are a number of reasons why large companies may be more likely to adopt a technology before small ones (Mansfield 1963b). Technologies may show positive scale effects in adoption, making costs and risks relatively lower for large companies. They are also more likely to have conditions suitable for adoption somewhere in their company, and have more frequent requirements for replacement. Many studies have provided empirical support for a positive link between firm size and initial adoption (Mansfield 1963b; Karshenas and Stoneman 1993; Battisti et al. 2007). We expect a positive relation.

The argument for a particular direction of influence between size and intensification is less clear-cut. The empirical literature does not give a clear guidance either. The early work by Mansfield (1963a) finds no significant effect of size on intensification rates, and the same result is in Battisti et al. (2007). However, Battisti and Stoneman (2005) find a positive relation, while Hollenstein and Woerter (2008) report mixed results and Fuentelsaz, Gomez, and Polo (2003) give a negative relation. We do not have prior expectations for the relation between size and intensification.

Start year

We measure a company's start year as the year it began operations in its country of residence. An older company may have more experience than a newer one, allowing

it to better assess new technologies and adopt them with less risk. However, it may be more institutionally committed to an existing technology. Battisti and Stoneman (2003) find that new firms have higher levels of intra-firm adoption than old firms, but Battisti and Stoneman (2005) find no significant relation. We do not have any prior expectations for the relation between start year and either interfirm or intrafirm diffusion.

Being part of a larger firm

We measure being part of a larger firm by a dummy taking the value of one if the company is part of a larger firm, and zero otherwise. Being a subsidiary may accelerate the initial diffusion of technology to a company. As larger firms are often found to be earlier adopters of a technology than smaller firms, subsidiaries may have earlier exposure to the technology than independent companies, and benefit from internal expertise in adoption in order to reduce costs, or have adoption mandated by central control. Antonelli (1985) finds that firms with highly centralised structures have accelerated diffusion of technology to different business functions. We therefore expect subsidiaries to have a higher rate of initial adoption. For intensification, these arguments still hold, and in Bocquet and Brossard's (2007) study independent companies have less intensive use. However, the local conditions for subsidiaries may be very different to those prevailing centrally, and so the initial exposure does not necessarily entail that subsequent intensification will be optimal or selected. We therefore expect no relation between being part of a larger firm and intensification.

Being foreign owned

We measure foreign ownership by the percentage of the company owned by private foreign individuals, companies, or organisations. Companies which choose to have an international presence are plausibly more willing and able to manage new technologies than businesses that stay at home. The literature on international (typically aggregated) technology diffusion suggests that foreign direct investment can result in technology spillovers (Keller 2004). Moreover, foreign owned companies have greater access to finance (Beck et al. 2006) and so greater ability to fund investment in technology, which is likely to be a particularly important factor on adoption in developing countries where institutional constraints on financing exist (Beck et al. 2006). We can reason in the same way as when a company is a subsidiary,

so that initial adoption would be increased by foreign ownership and intensification would be left unchanged, except that initial adoption is perhaps even more strongly increased due to the presumed innovativeness of companies with overseas operations, and their access to finance.

Being state owned

State ownership is measured by the percentage of the company owned by government. Government ownership may be less efficient than private ownership (Megginson and Netter 2001), and pressure to adopt new technologies may be lessened if, for example, there is less pressure to adopt them in response to commercial pressures. On the other hand, government ownership may bring access to foreign exchange necessary to purchase foreign technologies in the presence of capital controls, and other access privileges (Clarke, Cull, and Periá 2006). We do not take any prior position on how government ownership will affect initial adoption or intensification.

Financial obstacles

We measure the severity of financial obstacles faced by a company by a dummy variable dependent on how severe an obstacle is access to financing, including availability and cost. The dummy takes the value of one if a major or very severe obstacle is reported, and zero if the lower ratings of no obstacle, minor obstacle, or moderate obstacle are given. We also used fuller dummy sets and obtained similar results. If a company experiences difficulty accessing finance for new technology or finds it more expensive to finance, they are less likely to acquire it. The problems may be more difficult outside of the richest developed countries; Beck et al. (2006) report that lower levels of national financial and institutional development are associated with worsened financing problems for companies there. Battisti and Stoneman (2005) find that falling cost for a technology increases intensification, while in Fuentelsaz, Gomez, and Polo (2003) greater company liquidity accelerates it. However, for the technologies we consider, the biggest capital expenditure by far occurs with the initial adoption (for internet connection) and smaller expenditures are incurred by its various uses. Given that the initial expenditure has occurred, a company subject to financial constraints may wish to intensify their use as the various forms of internet communication are relatively cheap ways of undertaking business at

a distance. Thus, we expect financial obstacles to slow initial diffusion but increase intensification, in this case.

Power outages

Our next determinant variable is the number of power outages experienced by the company in a typical month over the last fiscal year. Power outages are a frequent occurrence in developing countries. For example, in the World Bank Enterprise Surveys used in this paper, Latin American and Caribbean companies have 1.9 outages per month on average. If there are more power outages, then a company may be more reluctant to adopt a power-dependent technology like the internet. Disruptions to internet access through power failure seem less likely to discourage use if the use is casual rather than for a systematic business purpose like maintaining client contact. We therefore expect power outages to be associated with lower intensification, but have no effect on initial adoption.

Power outages are potentially endogenous with internet initial adoption or intensification, since companies may acquire electricity in order to get internet access (and so outage counts may only increase from zero as the internet is acquired). We could not find a strong instrument that was also exogenous, and so we initially ran the equations without any instrumentation on our full sample. Power outages exerted no effect on initial adoption, and were associated with an increase in intensification. This latter result is best explained by the reverse causality, so companies that use the internet have electrical power more often which breaks more often. We address the endogeneity by restricting the sample to companies that are highly likely to use electricity irrespective of their internet usage. As this procedure greatly reduces the sample size, we report the results in section six looking at extensions to our model. In section five we exclude power outages as a determinant variable.

Competing against informal firms

We include a dummy variable equal to one if the company has competition from unregistered or informal firms, and zero otherwise. The informal sectors in developing countries, including in Latin America, are estimated to be far larger as a share of national output than those in developed countries (Schneider and Enste 2000), and so are likely to exert a much greater impact on business decisions. Formal sector

companies face costs that informal sector firms do not, including taxes, license fees, permit charges, notification fees, requirements for capital deposits, and costs arising from government inefficiency or corruption (González and Lamanna 2007). Informal rivals can produce without incurring these costs and so undercut the prices of formal sector companies. To maintain market share, formal sector companies would then have to reduce their price below the level that they would otherwise charge, leading to lower profit than in the absence of informal rivals, and giving them fewer retained funds to invest in new technologies. The funding constraints are likely to affect initial adoption of broadband internet, which can require quite heavy expenditure on training and computer hardware and software. Our expectation is that competition against informal firms will be associated with lower initial adoption.

It is less likely that intensification will be affected by competition from informal companies. Intensification of use of internet based business practices (in the form of purchasing, supplying, and undertaking R&D) has far lower requirements for capital expenditure than initial adoption of broadband internet. Intensification may therefore be affected to a lesser extent by declines in available funds caused by informal sector competitors. We expect competition against informal firms will have no association with a company's intensification of use.

Capital city

We include a dummy for whether the company is based in the capital city. A capital city may benefit from economies of scale in provision of goods and services. Additionally, the presence of a bias in developing countries towards policies supporting urban development in preference to rural development has been frequently argued (Bezemer and Headey 2008), which may manifest itself in provision of far better facilities than in rural areas. Thus, it may be less costly for companies to obtain internet connection. On the other hand, in a capital city it is likely to be much easier to interact face-to-face with suppliers and buyers compared with rural areas, so the internet may be used less as a means of connecting with them. We do not have an expectation on the link between being resident in a capital city and either initial adoption or intensification.

E-mail use

Another determinant is a dummy indicating whether the company uses e-mail. Using e-mail is likely to be a precursor technology to full internet adoption within a company, since e-mail is available publicly at internet cafes or from personal provision. Experience with a precursor technology should increase familiarity with the operation of the technology itself, and we expect it to influence positively both initial adoption and intensification. Hollenstein and Woerter (2008) find that use of a precursor increases e-commerce intensification.

Exporting

Our next measure is a dummy variable indicating whether the firm is a current exporter (either direct or indirect) and started exporting by the year 2000 at the latest. Exporters may learn about new technologies from their buyers, or may have to invest in new technologies to enter export markets. Some papers in the international technology transfer literature suggest that exporting boosts productivity (Blalock and Gertler 2004; Girma, Greenaway, and Kneller 2004), but the overall evidence is mixed (Wagner 2007). We expect no link between exporting and either initial adoption or intensification.

We selected the variable form to minimise its endogeneity in the estimation equation. We also considered the export share as a determinant. This quantity is likely to be endogenous, as the intensive use of internet technologies gives companies the ability to market their goods internationally. We looked for available instruments in our cross-sectional dataset, and found the most likely candidate to be the average number of days taken for exports to clear customs. While the exogeneity of this instrument was not rejected under a Wald test, it was found to be very weak by examination of first stage regressions, and resulting second stage estimates had no parameter certainty.

Industry use

A further determinant is the percentage of companies who have initially adopted the internet in the two digit International Standard Industrial Classification (ISIC) industry in which a company operates, calculated across all countries and excluding the company itself from the percentage. A company may learn from the initial adoption of other companies and emulate them. Battisti et al. (2007) find that initial

adoption of technologies by other firms in the same industry increases initial adoption by a company, with a weak negative effect on intensification. Hollenstein and Woerter (2008) find some evidence for the former link, and no evidence for the latter. We expect to see initial adoption within the industry affect a company's initial adoption positively, and leave the company's intensity of use unchanged.

Regional use

We include a variable equal to the percentage of companies who have initially adopted the internet in the region of the country in which the company is based, excluding the company itself from the percentage. Billón, Ezcurra, and Lera-López (2008) find that internet adoption is subject to geographic clustering, while in Baptista (2000) geographic proximity of previous adopters reduces the time until a company adopts. Our reasoning for the effect of regional use is the same as with industry use, and we expect regional use to influence positively initial adoption but not intensification.

Industry intensity

We measure industry intensity as the mean of the intensification variable defined above, where the mean is taken over all companies in the two digit ISIC industry in which the company operates, and across all countries. The mean is calculated by summing the variable for all companies in the industry and dividing by the number of companies in the industry, excluding the company itself from the calculation. In Hollenstein and Woerter (2008), intensification by other firms in the same industry tends to intensify a company's internet e-commerce use, but their initial adoption is unaffected. The same is found in Battisti et al. (2007). Our expectations are the same.

Regional intensity

We measure regional intensity as the mean of the intensification variable defined above, where the mean is taken over all companies in the region of the country in which the company operates. The mean is calculated by summing the variable for all companies in the region and dividing by the number of companies in the region, excluding the company itself from the calculation. The conditions that lead industrial intensity to influence company intensification, such as relevance of detailed experience and market standards, do not so clearly apply between companies who

`happen to be geographically located. So there is less reason to expect that regional intensity of use will influence intensification, and we expect it to have no relation with either intensification or initial adoption.

Country and sector dummies

Dummies are included for each country, which are intended to cover fixed effect differences in the national provision of the internet. We do not include dummies for a company's industry. Although industry dummies could capture the different rates of internet use across industrial sectors, the use and intensity of other companies in the industry are both included in the determinants so using industry dummies as well would cause perfect collinearity. We do include a dummy for whether a company is a manufacturer, with service sector companies as the reference group. When in section six we divide industrial use by country, we introduce industry dummies as perfect collinearity does not occur.

3. Data

The data used in this paper is from the World Bank Enterprise Surveys (www.enterprisesurveys.org). It consists of country-level surveys of companies, describing their characteristics and those of the business environment. We select the subset of surveys taken in Latin American and Caribbean countries (and listed in Appendix A). The surveys were undertaken in 2006 and 2009-10, with a much wider number of countries examined in the 2009-10 wave. We can not match companies that occur in both periods, so to avoid unrecognised duplication and to ensure common time effects throughout the data we use data from the last wave only.

The survey sample is drawn from lists of all eligible firms at the national statistic office, other government agencies, or sometimes from business associations or manual construction. The surveys use stratified random sampling, based on firm size, business sector, and geographic region, with a sample size per stratum sufficient to ensure a 7.5 percent precision in 90 percent confidence intervals. In our estimates, all standard errors are adjusted for the stratification. Company non-response is generally handled by substitution with other companies in the same stratum. There is some non-response for items within individual companies' responses. One way of handling item non-response would be to exclude the entire company response, which would

lose other item responses and may introduce bias if company non-response is correlated with the error term. We therefore impute the missing values using multivariate normal regression. The sample averages for our variables change little after inclusion of the imputed values, and our conclusions are largely unchanged with only minor shifts in statistical significance.

Companies are required to have at least five employees, and are drawn from the manufacturing and services sectors. Our final dataset is on companies in the ISIC codes 15-37, 45, 50-52, 55, 60, 63, 65, 70, and 72. There are 8,941 companies in total.

Table 2 shows the percentages of companies who have adopted the internet, and of these adopters, their distribution across the different levels of intensification of internet-based business practices. For the entire set of companies, the rate of initial adoption is high at 85.4 percent. The rate for small companies is lower, with over a quarter not using the internet, while most large companies have adopted it. The rate of initial adoption in the manufacturing sector is higher than that in the service sector.

In the set of all adopters, many companies have highly intensive use, with 78.7 percent using two or three internet-based business practices. Small companies have a lower rate of intensification, and large companies have a higher rate. Manufacturing has a higher level of intensification than the service sector. Thus, company size seems to exert a positive influence on initial adoption and intensification, and industrial sector also seems to affect them, with manufacturers having higher initial adoption and intensification than service companies.

[TABLE 2 ABOUT HERE]

Table 3 presents adoption rates by country, and the mean intensity levels for adopting companies in the countries. The adoption rates of surveyed companies are highest in South America, with near complete diffusion of broadband internet in Brazil and Ecuador. In Central America and the Caribbean the rates are generally lower, and just over a third of companies in Nicaragua have a connection. Intensity of use is more evenly distributed across the whole region, with the most use being made by Ecuadorian companies who usually employ all three commercial practices. The

adoption rates and mean intensities have a very low correlation coefficient of minus 0.05.

[TABLE 3 ABOUT HERE]

4. Econometric method

We estimate the initial adoption and intensification decisions as a probit and ordered probit system. The initial adoption decision variable y_i for company i is given by $y_i = 0$ if no initial adoption of the internet occurs and $y_i = 1$ if it does. It has a standard probit model:

$$y_i^* = x_i'\beta + \varepsilon_i$$

$$y_i = 0 \text{ if } y_i^* \leq 0 \text{ and 1 otherwise.}$$

where y_i^* is an unobserved latent variable, x_i is a vector of the explanatory variables including a constant term, β is a parameter vector, and $\varepsilon_i \sim N(0,1)$.

The intensification decision variable z_i is equal to zero, one, two, or three depending on how many of the internet-based commercial practices listed in section 2 (making purchases for the company, delivering services to clients, and undertaking R&D on new products and services) are adopted. By construction, the value of the variable z_i will be unique for each company, which we model using the ordered probit:

$$z_i^* = w_i'\delta + u_i$$

$$z_i = 0 \text{ if } -\infty < z_i^* \leq \mu_1$$

$$z_i = 1 \text{ if } \mu_1 < z_i^* \leq \mu_2$$

$$z_i = 2 \text{ if } \mu_2 < z_i^* \leq \mu_3$$

$$z_i = 3 \text{ if } \mu_3 < z_i^*$$

where z_i^* is an unobserved latent variable, w_i is a vector of the explanatory variables, δ is a parameter vector, and $u_i \sim N(0,1)$. In addition to the ordered probit, we also

considered an ordered logit and multinomial logit model. The results are reported in a working paper (Waters 2016), and show similar results to those here.

The intensification equation is potentially subject to a selection effect as the intensification choice is only observed if initial adoption occurs. If the error terms ε_i and u_i are correlated, the coefficient estimates in the intensification equation may be biased. The inverse Mills ratio correction can not be used here because of the non-linear form of the intensification equation (see Greene (2008), ch.24, on sample selection in non-linear models). Ideally, we would estimate the probit-ordered probit system simultaneously allowing for the correlation along the lines described in Greene (2008), but we encountered difficulties in achieving convergence in the resulting maximum likelihood estimation. However, we were able to calculate selection effects for slightly reduced systems. A high intensity decision variable was constructed with value of one if two or three internet-based commercial practices are adopted, and zero otherwise (the results were unchanged if three practices were required). The initial adoption and high intensity decision variables form a bivariate probit system which could be estimated. The error terms across the two equations were not significantly correlated, so we can have some confidence that the equations in our original initial adoption-intensification system can be treated as stochastically independent (as in Battisti et al. (2007) and Hollenstein and Woerter (2008)). We therefore estimate the initial adoption and intensification equations separately, and work with the intensification variable z_i taking a value of zero, one, two, or three.

The intensification equation may also be subject to a selection effect as some companies do not respond to questions on their use of internet based business practices, even though they indicate that they have adopted the internet. To investigate whether a selection effect was occurring, we ran an ordered probit model with Heckman sample selection taking intensification z_i as the determined variable, and restricted the sample to companies who have adopted the internet. We found that the correlation between the selection error and count error was not significantly different from zero, so the selection effect does not distort our results.

Endogeneity is another potential problem. As we have cross-sectional data, lagged variables are not available as instruments, and other variables in the dataset were usually found to be weak instruments for variables most likely to be subject to endogeneity. Accordingly, we have formulated the hypotheses in terms of variables that are less susceptible to endogeneity. The strongest candidates for endogeneity are exporting (since internet use may facilitate export promotion), e-mail use (since internet adoption allows e-mail to be used), and the number of power outages (since internet use may encourage electricity to be adopted if it has not already been). For exporting, our variable measures whether exports were occurring by the year 2000 and so before widespread adoption of the internet (source: databank.worldbank.org), so we consider endogeneity to be less of a problem. There are possibly some companies who were exporting in 2000 and stopped exporting by 2009-10 because they were not on the internet, which would be another route for endogeneity, but as exports and internet use were growing over the decade (source: databank.worldbank.org) this route is probably less important than internet use leading to exports. E-mail use seems highly likely to occur before more advanced applications of the internet, and is more widespread than internet adoption, so we do not consider endogeneity necessarily to be a serious concern here either. However, we also ran our regressions excluding exports and e-mail use, and found similar results to those reported here. To deal with possible endogeneity of power outage counts, we later restrict the sample to only the industrial sectors of metals and machinery, electronics, and chemicals and pharmaceuticals. Companies in these sectors require electricity independently of whether they also use the internet, so that the reverse causality from internet use to electricity adoption can be excluded. As the restriction to these industrial subsectors greatly reduces the sample size, we discuss these results only after our full sample estimates are presented.

The estimation is implemented in Stata code, available online in the working paper Waters (2016).

5. Results

[TABLE 4 ABOUT HERE]

Table 4 shows our results. There are some common factors influencing both initial adoption and intensification, but more distinct influences. The factors relating to national development are notably different in their effect. We describe in more detail all the estimated effects and how they compare with our expectations.

Company size has a positive effect on initial adoption but none on intensification. We expected the former finding, and left the impact on intensification open to empirical determination. Firm age has no significant link with initial adoption or intensification. We did not have any prior expectation on the links. Manufacturing companies have no difference in their rates of initial adoption compared with service companies, but lower levels of intensification.

In the ownership variables, being part of a large firm increases initial adoption and leaves intensification unchanged, and both links were anticipated. The foreign ownership share has no effect on initial adoption whereas we expected a positive effect, and it has a negative effect on intensification while we expected no effect. The results are consistent with a foreign owner providing the results of internet usage to a subsidiary instead of the subsidiary using it themselves. The state ownership share has no effect on either form of adoption, and we had no prior expectations about it.

In the national development variables, financial obstacles are associated with no change in initial adoption and an increase in intensification; we expected the latter link, but thought there would be a negative impact on initial adoption. When companies compete against informal businesses, initial adoption is reduced and intensification is not affected, as we expected. Being in a capital city lowers initial adoption and there is no link with intensification. We did not have any prior expectation of the direction of any connections.

Among the epidemic effects, e-mail use is associated with increased initial adoption and intensification, as expected. Exporting has a positive effect on initial adoption, where no link was anticipated, but has no link with intensification as expected. Industry use does not change initial adoption, where we expected a positive relation, and does not affect intensification either, which was expected. Use in the region increases initial adoption but doesn't affect intensification, as expected. Industry

intensity has no relation with initial adoption and increases intensification, which we thought would occur. Regional intensity has no effect on either form of adoption, as anticipated.

Overall, initial adoption is influenced by a number of rank factors: the commonly identified factors of company size and membership of a larger firm, and factors relating to national development (informal sector competition, and being in a capital city). Among the epidemic effects, initial adoption is influenced by internal experience with e-mail, exporting, and use by other companies in the same region. Intensification is influenced by the rank factors of foreign ownership (among the ownership factors) and financial obstacles (among the national development variables). However, the effect of the rank variables is generally weaker for intensification than for initial adoption. The epidemic influences on intensification are experience with e-mail and industry intensity. Thus, the variables that determine initial adoption are largely distinct from those that determine intensification.

Do the determinants of initial adoption and intensification previously identified as applying in highest income countries also apply in poorer countries?

We can answer our question of whether the determinants of initial adoption and intensification previously identified as applying in highest income countries also apply in poorer countries. Company size is a positive influence on initial adoption as in much of the literature (for example, Karshenas and Stoneman (1993)), but not on intensification as in Battisti et al. (2007) (although the literature findings are not strong). Firm age does not affect intensification, echoing the findings of Battisti and Stoneman (2005). We find that being part of a larger firm is associated with higher initial adoption, consistent with Antonelli's (1985) finding on the impact of highly centralised structures, while it has no effect on intensification in contrast to Bocquet and Brossard's (2007) finding of reduced ICT intensification. Foreign ownership is associated with reduced intensification only. Our result is perhaps surprising given the importance of foreign direct investment for technology transfer in the aggregate technology diffusion literature, but has similarities with Hollenstein and Woerter's (2008) finding that initial adoption of e-commerce is reduced by foreign ownership. Prior experience (with e-mail) increases both initial adoption and intensification, with the latter finding similar to Hollenstein and Woerter's (2008) result on the effect of

internet e-commerce precursors on intensification. Industry use has no effect on a company's use, contrasting with Battisti et al.'s (2007) finding of a positive link, and industry intensity increases a company's intensity, in line with the results found in the literature (Battisti et al. 2007; Hollenstein and Woerter 2008). Thus, many of the causes of initial adoption and intensification that we find are similar to those in the prior literature, but there are some significant departures.

What other determinants are significant in these poorer countries?

We can also answer the question of what other determinants are significant in countries poorer than those previously examined in the intra-firm diffusion literature. Among the rank effects, state ownership is insignificant in its effect on either form of adoption. Among the variables relating to national development, financial obstacles have no effect on initial adoption and increase intensification. Our intensification result contrasts with Battisti and Stoneman's (2005) finding that higher costs reduce intensification in the UK. However, in their case, costs apply only to the technology under consideration, whereas in our case financial constraints apply equally to expenditures other than technological purchases. The intensification of internet use feasibly brings cost savings for business interactions relative to alternative technologies such as face-to-face meeting, so that financial constraints can make technological intensification relatively more valuable.

Competition against informal firms is associated with reduced initial adoption but unchanged intensification. We read the results as indicating either that capital accumulation for technology purchases can be difficult in markets with many low cost competitors, or that markets with informal competition often have low entry costs and do not readily benefit from internet adoption. Being in a capital city reduces initial adoption without effect on intensification, consistent with the idea that dense personal interactions in urban areas (and capital cities in particular) can substitute for interaction via the internet.

Of the epidemic effects less commonly studied in the literature on intensification of use of an individual technology, regional use and exporting affect initial adoption, although regional intensity does not. Exporting has no effect on intensification, echoing the mixed findings in the aggregate technology diffusion literature. Regional

use is positively related with initial adoption, consistent with Billón, Ezcurra, and Lera-López (2008) and Baptista (2000). Regional economic connections may be more important in developing countries where limited national infrastructure or high transport costs limit national connections. However, regional intensity has no effect on intensification, suggesting that there is a limit to the relevance of experience of geographic neighbours when it comes to advanced use of the internet.

6. Extensions

6.1 The effect of power outages

In this section we consider several extensions to our base model. In the first extension, we consider how power outages affect initial adoption and intensification. Section two suggested that power outages are expected to be associated with lower intensification, but to have no effect on initial adoption. However, the variable is likely to be endogenous because companies that adopt the internet may adopt electricity in order to do so, and then experience power outages. Our uncorrected estimates suggested that this reverse causality was dominating the results. To deal with issue, we ran the estimations using only companies in the metals and machinery, electronics, and chemical and pharmaceutical sectors. These companies employ electricity heavily, and so are likely to adopt electricity irrespective of their internet use. Thus, for them power outages are far less likely to be endogenous. Columns two to five of table 5 show the results. Power outages have no effect on either adoption or intensification. We expected the former result, but thought that outages may reduce intensification.

6.2 Are regional effects incorrectly assigned to industrial effects?

In section five we found that regional use is associated with increased initial adoption by a company. As industries are often clustered in a region, it is possible that some of the importance of industrial adoption in explaining adoption (found in Battisti et al. (2007), for example) may be due to regional effects operating in the presence of industrial clustering. To investigate this hypothesis in Latin America and the Caribbean, we re-ran the model excluding regional use and intensity. If the impact of industrial adoption is picking up the impact of regional adoption, then we would expect that the coefficients on industrial use and intensity would change substantially in value or significance between the estimations with and without regional effects.

The results are shown in columns six to nine of table 5. The coefficient measuring industrial use's effect on a company's adoption and the coefficient measuring its effect on a company's intensity remain negligibly low and insignificant. The coefficients measuring industrial intensity's effect on a company's initial adoption and intensification change little in value and significance. Thus, industrial and regional experience seem to have distinct effects on both initial adoption and intensification.

6.3 How do experience effects change when industrial competition is tighter?

In section two we said that we did not distinguish between epidemic effects on one hand and stock effects on the other, given the variables we employed. The variables of industry use and intensification were used to measure these net effects of industry on company adoption. Here, we change the variables so as to make stock effects more significant relative to epidemic effects. The variables are defined for industrial use and intensification in the countries where a company is based, rather than internationally across the whole Latin America and the Caribbean region. The idea is that other companies in the same industry and country will be close competitors to the original company, and so the company's technology decisions will take into consideration how to gain a market advantage over these rivals.

Columns ten to fourteen of table 5 show the results of the regression. Industrial use and intensity remain insignificant in their effect on a company's initial adoption. Thus, stock effects on initial adoption are no more important relative to epidemic effects when national industrial influence is considered rather than international industrial influence. However, industrial intensity is no longer a significantly positive influence on a company's intensification when the industrial intensity is defined at a country level. It seems that at a national level, stock effects become more important relative to epidemic effects when it comes to intensification.

[TABLE 5 ABOUT HERE]

7. Conclusions

In this paper we have examined the determinants of initial adoption and intensification of business use of the internet in countries with less economic

development than those previously examined in the literature. A cross-sectional dataset of Latin American and Caribbean companies was used for investigating the relevance and impact of the determinants. We found that many of the determinants previously used in the inter-firm and intra-firm literature for the highest income countries continue to be relevant in lower income countries. We also found that other variables relating to the level of national development are helpful in explaining use, and foreign ownership and the level of adoption in the region in which the company is resident are also important.

There are many policy implications that can be tentatively drawn from the study. State ownership is not found to be adverse for initial adoption or intensification of internet usage, and nor are power outages. However, encouragement of larger shares of foreign ownership in the economy may be associated with reduced intensification of use. Financial obstacles are associated with increased intensification. We attribute the intensification to companies seeking to economise on communication costs, so that a government may support the development of the internet to mitigate financing constraints in an area.

Businesses in competition with informal firms have lower initial adoption but unaffected intensification, which is plausibly due to lower levels of accumulated funds in such businesses. For these businesses, extension of finance may allow them to overcome funding constraints. Facilitating initial access to the internet (either by individual or collective routes) may then result in intensive use without more support, as intensive use is likely to occur at a lower cost than initial adoption. Experience with e-mail is associated with increased initial adoption and intensification. Providing facilities for access to e-mail may support subsequent use of the internet. Another finding is that capital cities have a lower rate of internet adoption. It may be that this result arises because they have more face-to-face interaction, and the internet is a substitute for it in less urbanised areas. Supporting internet supply and acquisition in rural areas may be a way of allowing rural companies to interact more fully, as is possible in capital cities.

Regional use increases initial adoption. If companies could use the technology profitably but have not already done so, then initial adoption may be encouraged by

supporting the co-location with other companies who have already adopted. Whether the internet is then intensively used does not depend on regional use, so the clustering acts only as a seeding method for the technology.

Further work could examine to what extent industrial epidemic effects are partially attributable to regional effects. This paper indicates that for our dataset of Latin American and Caribbean companies, a company's initial adoption of a technology is influenced by the technology's use in other companies in the region, rather than its use in industry more widely. In other data the effects may overlap, raising the possibility that industrial epidemic effects previously identified in the literature may be more correctly ascribed to regional effects. The regional effects may be stronger in lower income countries where communications networks are not as developed as in the highest income countries.

Future work could also look at the relative impact of epidemic and rank effects in highest income regions, by comparison with lower income regions. As information may move more fluently in higher income countries, epidemic effects are perhaps relatively more important than rank effects there compared with lower income countries. Finally, the initial adoption of internet technology examined here and its intensification require different levels of capital expenditure. Future work could examine adoption of a technology whose price does not vary across the initial adoption and intensification stages, such as a homogenous capital good.

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Appendix A

[TABLE A1 ABOUT HERE]

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Table 1, part i

Explanatory variables and their expected effect

Variable	Description	Expected sign: initial adoption / intensification [a]
Rank effects		
Company size	Dummies for medium (20 to 99 employees) and large companies (100 or more). Reference group is companies with 19 or fewer employees.	+ / ?
Start year	The year in which the company began operations in the country	? / ?
Ownership		
Part of larger firm	Is the company part of a larger firm? (yes = 1, no = 0)	+ / 0
Foreign owner share	Percentage of company owned by private foreign institutions (0 to 100)	+ / 0
State owner share	Percentage of company owned by a government (0 to 100)	? / ?
National development		
Financial obstacles	Is access to financing a major or very severe obstacle to operations? (yes = 1, no = 0)	- / +
Power outages	Over the last fiscal year, what was the typical number of monthly power outages?	0 / -
Compete against informal firms	Does the company compete against unregistered or informal firms? (yes = 1, no = 0)	- / 0
Capital city	Is the company resident in the capital city? (yes = 1, no = 0)	? / ?
Epidemic effects		
Internal experience		
E-mail use	Is e-mail used in communication with clients or suppliers? (yes = 1, no = 0)	+ / +

Table 1, part ii

Explanatory variables and their expected effect

International experience		
Exporter in 2000	Is the company a current exporter which started exporting by the year 2000? (yes = 1, no = 0)	0 / 0
Initial use		
Industry use	Proportion of other companies using the internet in the same two digit ISIC industry (0 to 1)	+ / 0
Regional use	Proportion of other companies using the internet in the same region in the country (0 to 1)	+ / 0
Intensity		
Industry intensity	Average intensity of use by other companies in the same two digit ISIC industry (0 to 1)	0 / +
Regional intensity	Average intensity of use by other companies in the same region in the country (0 to 1)	0 / 0

[a] + denotes a positive expected effect, - denotes a negative expected effect, 0 denotes no effect, and ? denotes that the theory gives an ambiguous prediction.

Table 2

Number of companies who use the internet and the level of their intensification

	Number of users and non-users	Internet use (% of all companies)		Number of internet-based business practices (% of users)			
		Non-users	Users	0	1	2	3
All companies	8941	14.6	85.4	4.7	15.4	27.8	50.9
By size							
Small companies	3269	28.4	71.6	6.3	18.7	29.9	44
Medium companies	3217	9.8	90.2	3.7	15	27.8	52
Large companies	2455	2.7	97.3	4.2	12.7	25.8	56.4
By sector							
Manufacturing	6521	13.3	86.7	3.9	14.6	27.4	53.2
Services	2420	18.2	81.8	6.7	17.6	29.1	44.3

Small companies have 19 or fewer employees, medium companies have 20 to 99 employees, and large companies have 100 or more employees.

Table 3

Company internet use and level of intensification, by country

	Internet use (% of companies)	Number of practices (mean average among companies who use the internet)
Argentina	90.7	2.3
Bolivia	86.8	2.4
Brazil	96.6	2.3
Chile	86.4	2.2
Colombia	95.1	2.1
Costa Rica	82.3	1.9
Dominican Republic	78.8	2.1
Ecuador	96.0	2.6
El Salvador	80.2	2.3
Guatemala	68.9	2.2
Honduras	59.9	2.1
Jamaica	64.3	2.2
Mexico	77.2	2.0
Nicaragua	36.4	2.5
Panama	60.0	2.1
Paraguay	83.7	2.0
Peru	82.4	2.0
Trinidad and Tobago	69.9	2.4
Uruguay	76.4	2.1
Venezuela	77.0	1.7
LAC region	84.2	2.2

Table 4

Results for estimations of initial adoption and intensification

	Initial adoption		Intensification	
	Coeff.	St. error	Coeff.	St. error
Rank effects				
Company size				
Medium co	0.472***	0.123	-0.027	0.130
Large co	0.858***	0.220	0.176	0.196
Start year	-0.007	0.004	-0.002	0.003
Manufacturing	-0.281	0.182	-0.38**	0.173
Ownership				
Part of larger firm	0.659***	0.230	-0.005	0.143
Foreign owner share	0.004	0.003	-0.006**	0.002
State owner share	-0.042	0.038	-0.039	0.031
National development				
Financial obstacles	-0.085	0.123	0.259**	0.131
Compete against informal firms	-0.287*	0.161	-0.034	0.131
Capital city	-0.242*	0.131	0.061	0.126
Epidemic effects				
Internal experience				
E-mail use	2.163***	0.160	1.615***	0.328
International experience				
Exporter in 2000	0.285*	0.164	0.170	0.117
Initial use				
Industry use	-0.110	1.087	-0.642	1.208
Regional use	3.368***	0.687	-0.030	0.708
Intensity				
Industry intensity	0.193	0.672	2.798***	0.907
Regional intensity	-0.656	0.465	0.215	0.514
Country dummies	Yes		Yes	
N	8941		7541	
F test	F(35,8906)=18.143; p=0		F(35,7506)=3.657; p=0	

The dependent variable for initial adoption is a dummy for whether the company has an internet connection, and for intensification is an ordinal (an integer from zero to three) measuring how many internet-based business practices it uses. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 5, part i

Extensions

	With power outages				No regional effects				Industries divided by country			
	Initial adoption		Intensification		Initial adoption		Intensification		Initial adoption		Intensification	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Rank effects												
Company size												
Medium co	0.425**	0.172	-0.131	0.135	0.484***	0.121	-0.022	0.131	0.504***	0.109	0.123	0.117
Large co	0.791***	0.241	-0.276	0.224	0.703***	0.193	0.184	0.203	0.854***	0.225	0.231	0.171
Start year	0.004	0.005	-0.005	0.004	-0.006	0.004	-0.002	0.003	-0.003	0.003	-0.005*	0.003
Manufacturing	-0.023	0.770	-0.502	0.673	-0.231	0.181	-0.387**	0.178	0.782**	0.347	-0.907***	0.339
Ownership												
Part of larger firm	1.221**	0.491	0.428***	0.165	0.626***	0.230	-0.006	0.142	0.857***	0.209	0.024	0.135
Foreign owner share	0.003	0.004	-0.002	0.002	0.005*	0.003	-0.006**	0.002	0.002	0.002	-0.006***	0.002
State owner share	0.016	0.015	-0.016	0.022	-0.04	0.039	-0.039	0.030	-0.047	0.040	-0.006	0.021
National development												
Financial obstacles	-0.138	0.184	0.415***	0.153	-0.095	0.122	0.255*	0.133	-0.03	0.109	0.227*	0.117
Power outages	0.042	0.025	0.003	0.010								
Compete against informal firms	-0.303*	0.156	0.382***	0.141	-0.286*	0.161	-0.036	0.131	-0.269*	0.152	0.054	0.113

Table 5, part ii

Extensions

Capital city	0.33*	0.173	-0.165	0.132	-0.119	0.130	0.062	0.126	-0.221*	0.123	-0.11	0.105
Epidemic effects												
Internal experience												
E-mail use	2.06***	0.284	0.531	0.484	2.159***	0.161	1.616***	0.327	2.041***	0.147	1.667***	0.333
International experience												
Exporter in 2000	0.075	0.239	0.011	0.178	0.327**	0.164	0.168	0.117	0.339**	0.148	0.176	0.108
Initial use												
Industry use	-0.962	1.765	-1.137	1.449	0.086	1.073	-0.633	1.203	0.331	0.642	0.613	0.541
Regional use	2.502*	1.442	-1.61	1.372					3.373***	0.738	-0.516	0.594
Intensity												
Industry intensity	6.124***	1.936	0.907	2.210	0.126	0.677	2.823***	0.902	0.211	0.282	0.096	0.186
Regional intensity	-0.231	0.991	0.262	0.784					-0.702	0.477	0.499	0.495
Country dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry dummies	No		No		No		No		Yes		Yes	
N	2051		1883		8941		7541		8789		7465	
F test	F(35,2016)=5.156; p=0		F(35,1848)=1.952; p=0		F(33,8908)=18.420; p=0		F(33,7508)=3.801; p=0		F(58,8731)=11.880; p=0		F(64,7401)=10.949; p=0	

The dependent variable for adoption is a dummy for whether the company has an internet connection, and for intensification is an ordinal (an integer from zero to three) measuring how many internet-based business practices it uses. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table A1

Countries in our sample

Argentina
Bolivia
Brazil
Chile
Colombia
Costa Rica
Dominican Republic
Ecuador
El Salvador
Guatemala
Honduras
Jamaica
Mexico
Nicaragua
Panama
Paraguay
Peru
Trinidad and Tobago
Uruguay
Venezuela