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The decision to innovate or to adopt existing technologies is driven by productivity levels. Large productive incumbents may have an advantage over new entrants and laggards and lead innovation, yet depending on the type of technology, the latter may catch up by pursuing more advanced technologies. Different technologies can therefore widen or shrink the distribution of productivity across firms (Benhabib et al., 2021). Using a novel dataset of around 60,000 Spanish firms from different industries between 2017-2019, we show that investment in a particular technological innovation – online sales – is indeed pursued by the sector's most productive and largest firms, yet laggard firms do try to catch up by investing more in new technologies, despite starting at lower productivity levels. This suggests that costly innovation and easy adoption may actually curb overall productivity growth as more firms' free ride on innovation efforts by the leaders in each sector.

Keywords: innovation, adoption, diffusion, probit, productivity, ICT.

JEL codes: O31; O34; O41; O47; L16.

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I. Introduction

Adoption of new technologies is generally believed to have a positive impact on productivity (Cardona, 2010; Gómez-Barroso, 2020; Vu, 2020). Competition between firms push them to generate new innovations, or to adopt existing ones, to keep ahead of the sector or industry in which they operate. Much of the empirical research on Information and Communications Technologies (ICT) investment impacts searches for such productivity gains, yet its findings are not conclusive and rather disappointing (DeStefano, 2018; Bertschek, 2013 and Aral, 200), with some authors claiming the productivity effect cannot be found in the data. Certain conditions must be first met before new technologies can fully deliver the expected gains (Brynjolfsson, 2018; Corrado, 2021; Storm, 2022). This was originally established by the so-called Solow Paradox (Solow, 1987)

Literature describes technological adoption as the process by which a company or sector incorporates the necessary means to use a specific tool in their daily operations. Diffusion would then be described as the process by which a specific technology is adopted and used in an organization or sector until a certain number of users internalize and transfer their acquired knowledge to their peers or to other companies (Peansupap, 2005).

The empirical literature that examines the joint effect of productivity dynamics in firms is rather disparate. A first strand has used Technology Acceptance Models (TAM) and Technology Adoption and Usage Tool (TAUT) models to look at what drives firms' adoption of specific ICT technologies (Gangwar, 2014), like a website (Lederer, 2000). TAM models and its extended versions have high capability to explain the technology adoption while the significance of Technology-Organization-Environment framework is similarly recognized in explaining technology adoption.

Very specifically, some papers have looked at the drivers of starting online sales and e-commerce, both from the users and firms' perspectives (Fayad, 2015; Klopping, 2004; Fedorko, 2018; Han, 2009, Haryanti, 2020, Hong, 2006). Research finds that web functionalities, web spending, and integration of externally oriented inter-organizational systems tend to be the most influential drivers in firms' e-commerce adoption, while firm size, partner usage, electronic data interchange usage, and perceived obstacles negatively affect migration to e-commerce.

A second strand has looked at how technology diffuses across firms. According to Karshenas (1995) there are five sub-models that explain technological diffusion: rank, epidemic, location, stock, and order effects. With reference to rank models, research focuses on the connection between various business characteristics, returns differentials, and adoption choices. Size is related to lesser risk aversion and fewer financial limitations. Since a better educated workforce helps the early adoption of innovations, human capital is typically measured by the percentage of trained people (Chun, 2003). According to theory on global involvement, businesses that engage in international trade have a higher likelihood of implementing new technology (Haller, 2011; Hollerstein, 2004; Lucchetti, 2004). Early adopters propagate innovations and encourage other businesses to adopt the same technology and to provide more information, which is how epidemic models compare innovations' diffusion to the spread of a virus. Regarding location, the empirical literature finds evidence that urban or densely populated locations facilitate digital adoption. Stock models presuppose that as the proportion of past adopters rises, adoption's advantages diminish. When profits rely on the order of adoption, order models stress the advantages for early adopters.

A third strand has looked at the effects of how technology adoption and innovation drives productivity. The literature outlines many ways that digitization might improve business performance. By embracing digitization, organizations can cut costs related to communication, including contacts with customers, suppliers, and other companies (Jorgenson, 2001). It also makes internal communication inside the company more effective (Heredia et al., 2022; Benitez et al., 2022). Additionally, digitalization might result in the adoption of new procedures, practices, and production techniques within the company (Mack and Faggian, 2013; Zhai et al., 2022). As a result, these changes are anticipated to boost productivity and encourage the development of innovative company models.

From the point of view of aggregate economic growth, a recent literature has explored the role of productivity from different perspectives. The Schumpeterian growth paradigm sheds light on some of the key aspects driving innovation, firm dynamics, and economic growth. Schumpeter's idea of creative destruction—the process by which new inventions replace older technologies—has been "operationalized" in two ways by the Schumpeterian growth theory (Aghion, 2015). The first one has created models based on creative destruction that throw light on a number of microeconomic aspects of the growth process, particularly the role of competition, firm dynamics, and cross-firm and cross-sector reallocation. Second, in order to compare predictions that set it apart from other growth theories, it has made extensive use of microdata, particularly on entry, exit, and firm size distribution. More details on the Schumpeterian paradigm applied to the relationship between growth, innovation and firm dynamics can be found in Aghion (2014), Bloom (2019), Garcia-Macia (2019), Kerr (2014) and Klette (2004).

Firms' decision to innovate or to adopt existing technologies depends on expected returns. Benhabib et al. (2021) develop a model of endogenous innovation diffusion across firms in which laggards catch up by adopting more advanced technologies originally invented by high-productivity leaders in the sector. Leaders may drag productivity levels – and hence spur economic growth – by innovating more, yet their incentives to innovate are limited by the cost of innovation and the ease with which laggards may catch up. Costly innovation and easy adoption may curb productivity growth as more firms' free ride on innovation efforts by the leaders in each sector.

In Acemoglu and Cao (2015), incumbents that are leaders in their sector are challenged by entrants that leapfrog productivity with a radical innovation. While incumbents invest in incremental R&D to raise productivity and grow, potential entry of small new firms may undermine those efforts as they catch up and eventually replace some incumbents.

This paper tests these propositions of the Schumpeterian endogenous growth literature by examining a specific technological innovation – online sales – through the microdata of a large dataset of Spanish firms (more than 60,000) between 2017-19. We consider the endogeneity of incentives to adopt technologies with a heckman probit model. The main finding is that laggard firms do try to catch up by investing more in new technologies, despite starting at lower productivity levels. This strongly depends, however, on the type of sector, and on the particular type of technology, as well as the specialization in B2B or B2C, confirming the arguments of Benhabib et al. (2021).

This paper is structured as follows. Section 2 discusses the details of the database, and the methods we employ to test the hypothesis that leaders or followers are faster at adopting new technologies. Section 3 discusses the main results and a few robustness checks. Section 4 concludes.

II. Testing technology adoption

A. The INE database

The database comes from the Survey on the Use of Information and Communication Technologies and Electronic Commerce in Companies, developed by the Spanish's national statistics body (INE) in 2015. This survey has been harmonized with that of other European countries through Eurostat. It is conducted annually since 2017, and at present covers three years, till 2019. The database includes approximately 20,000 firms per wave, and firms surveyed in one year differ from previous waves.

The dataset was set up to inquire on the use of IT investment in small and large firms hence it contains a series of variables asking specific questions on the IT use and ICT expenses, as well as specific new technologies in which the firm invests, such as online sales, the use of websites, cloud computing, Big Data or investment in the Internet of Things. The database is confidential and some questions just ask for categorical answers, rather than detailed numerical ones.

B. Some basic statistics

The dataset we use includes 56,438 firms in total. We have eliminated outliers from the database by taking out firms that reported inconsistent answers in different parts of the survey.

Firms differ in their characteristics. Company size is determined by the number of employees; however, the survey just asks to report size in one of four categories, between micro-firms with less than 10 employees, and SME (10 to 49 employees), and medium (50-249 employees) and large firms (250+ employees). A major feature is that the dataset is biased towards larger firms: in Spain, small companies represent the majority (%), but these firms are two thirds of our sample only. In particular, 19,477 (34.51%) are micro-firms with less than 10 employees, and 18,500 (32.78%) are small firms. The other third is composed of medium to large firms, with 10,828 (19.19%) medium firms and 7,633 (13.52%) large firms.

The sample is also composed of different economic sectors, in manufacturing, construction, and services industries.[1] The most represented industry in our sample is retail trade (11.08% of firms), followed by construction (9.95%), wholesale trade (9.27%), food, tobacco, textile, wood and derivatives (9.25%), administrative activities (9.20%), transport (8.38%), real estate (7.34%), while the remaining economic sectors represented account for less than 6% each. This is slightly different from the total of Spanish firms which is more concentrated in some of the subsectors. While not representative for the entire economy, it does give a more balanced view on different sectors.

The survey asks company representatives general questions about their activities, such as turnover and size. These variables are categorical, hence no precise number is provided. The survey also asks about innovation efforts in different ways. One is the adoption of different technologies, in particular related to ICT. On the one hand, the survey also has a particular interest in the use of online sales or purchases, or the adoption of a webpage, social media or even AI. On the other hand, it also asks for investment in ICT, not just in equipment but also in personnel and in training.

[1] No agricultural firms are included in the survey conducted by the INE.

Table 1. Variable description

Variable	Description
Online sales	Dummy variable that takes value of 1 if the firm has purchased goods or services through e-commerce (website or apps), and 0 otherwise. Orders delivered by e-mail are excluded.
Productivity	Annual firm revenues per employee (excluding taxes). In million euros.
ICT expenditure	Annual expenditure per employee in ICT goods and services. In million euros.

For our purposes, we focus on the few variables we include in our model, and that look into the effect of productivity, size, and sector on the adoption of a certain technology by the firm.[2] We look first at the adoption of online sales. The survey asks firms for the percentage sales they realize online. The question purposely excludes the use of e-mail to place orders to providers, as it is not considered e-commerce. Not many firms actually sell online (Table 2), and on average it just represents 7% of total sales. The use of e-commerce by Spanish firms varies considerably by different groups of firms, being the larger ones the more prone to use this technology. Micro firms are especially low intensive in online purchases, with only 20.21% of the surveyed ones declaring to use it. This percentage increases significantly for small (32.14%), medium (37.75%) and large (41.24%) firms. In any case, it is still worth to point out that most firms do not purchase online. We transform online sales into a binary indicator which is 1 for those firms that sell more than 90% goods and services through website or e-commerce apps.

Table 2. Baseline stats per size.

	micro	**small**	**medium**	**large**
% of firms				
online sales (% of firms)	20.21	32.14	37.75	41.24
online sales (% of sales)	6.47	6.65	6.28	7.10
productivity	0.087	0.162	0.205	0.217
ICT expenditure	0.6	0.8	1.9	3.6

The adoption of e-commerce is very different across sectors, as reported in Table 3. Naturally, more intensive firms in online sales are those related to the information and communication

[2] Table 1 presents the definition for the main variables included in our model.

industry, where more than half of the surveyed firms declare to use this technology to conduct purchases. Next, professional activities also show good levels of e-commerce penetration, with over 46% of firms using it. On the other end, transport firms are the less intensive in online sales, with less than 20% of firms declaring to purchase online. By size, usually the larger firms within each economic industry are more likely to use online sales, although some exceptions arise, for instance in information and communication are the smallest the more intensive, while for the case of professional activities, real estate, accommodation, metal and vehicles industries the more intensive are the medium companies.

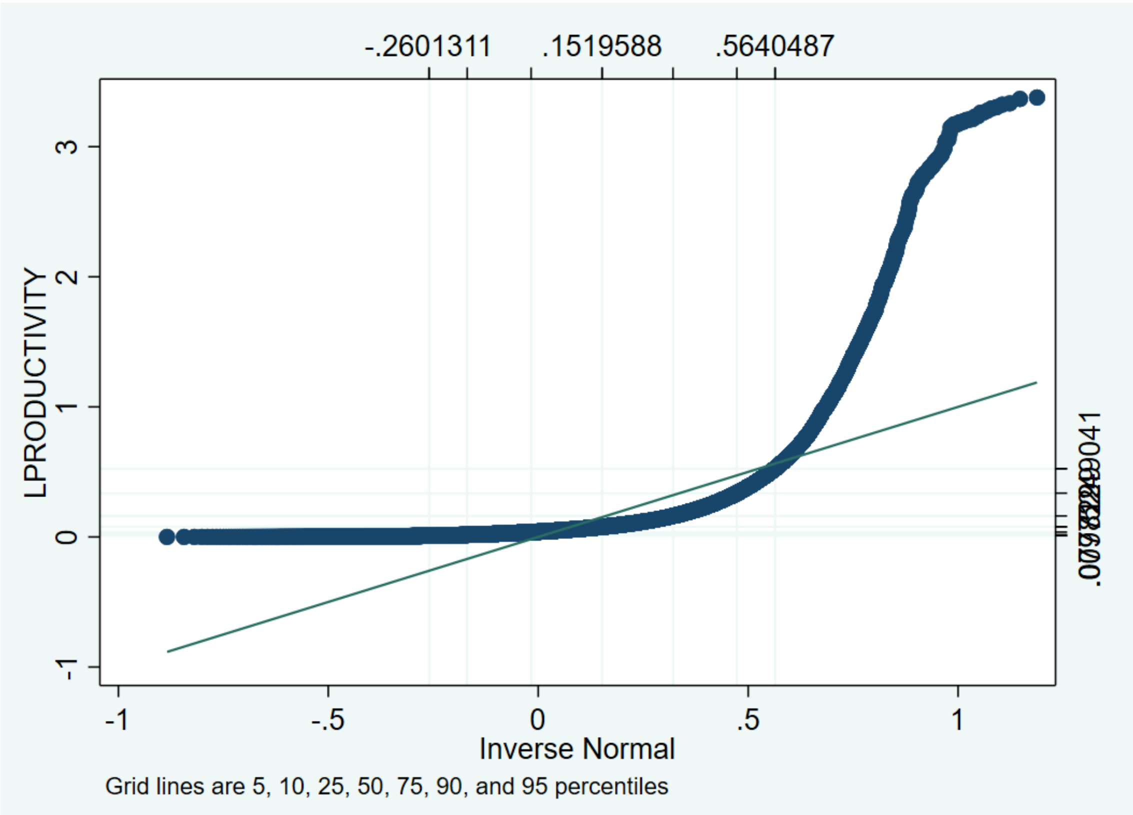
Table 3. Baseline ecommerce stats for database, per size and sector.

Sector (CNAE)	*all*	*micro*	*small*	*medium*	*large*
10 Commerce	25.54	18.75	24.15	34.36	41.03
19 Chemistry	35.81	n.a.	25.72	40.00	48.65
24 Metallurgy	29.98	n.a.	22.13	38.66	33.64
26 IT	39.46	n.a.	35.39	42.75	40.22
35 Utilities	24.39	5.13	26.73	22.10	39.66
41 Construction	22.05	13.00	25.56	33.94	39.31
45 Car sales	36.69	28.07	42.17	46.33	49.83
46 Retail (large)	29.82	19.75	31.03	35.34	44.87
47 Retail (small)	25.15	18.84	32.17	30.88	39.40
49 Transport	19.34	7.65	22.33	28.40	33.99
55 Lodging	36.38	31.18	38.97	41.01	32.20
58 Info/comunication	53.39	47.70	56.67	56.59	55.65
68 Real Estate	22.40	19.64	31.17	33.50	33.33
69 Services	46.26	n.a.	42.74	49.13	48.84
77 Administration	31.80	25.19	33.20	31.14	36.15

To measure productivity, we can only use total (pre-tax) sales per worker, which is the only variable reported by INE. While turnover is better measured by labor productivity or a TFP measure, turnover is typically closely correlated with these measures (Syverson, 2011). Productivity displays the typical S-shape, with many firms displaying (very low) productivity, and few firms at the top. In fact, half of the firms have a productivity below 0.15, and the top 2%

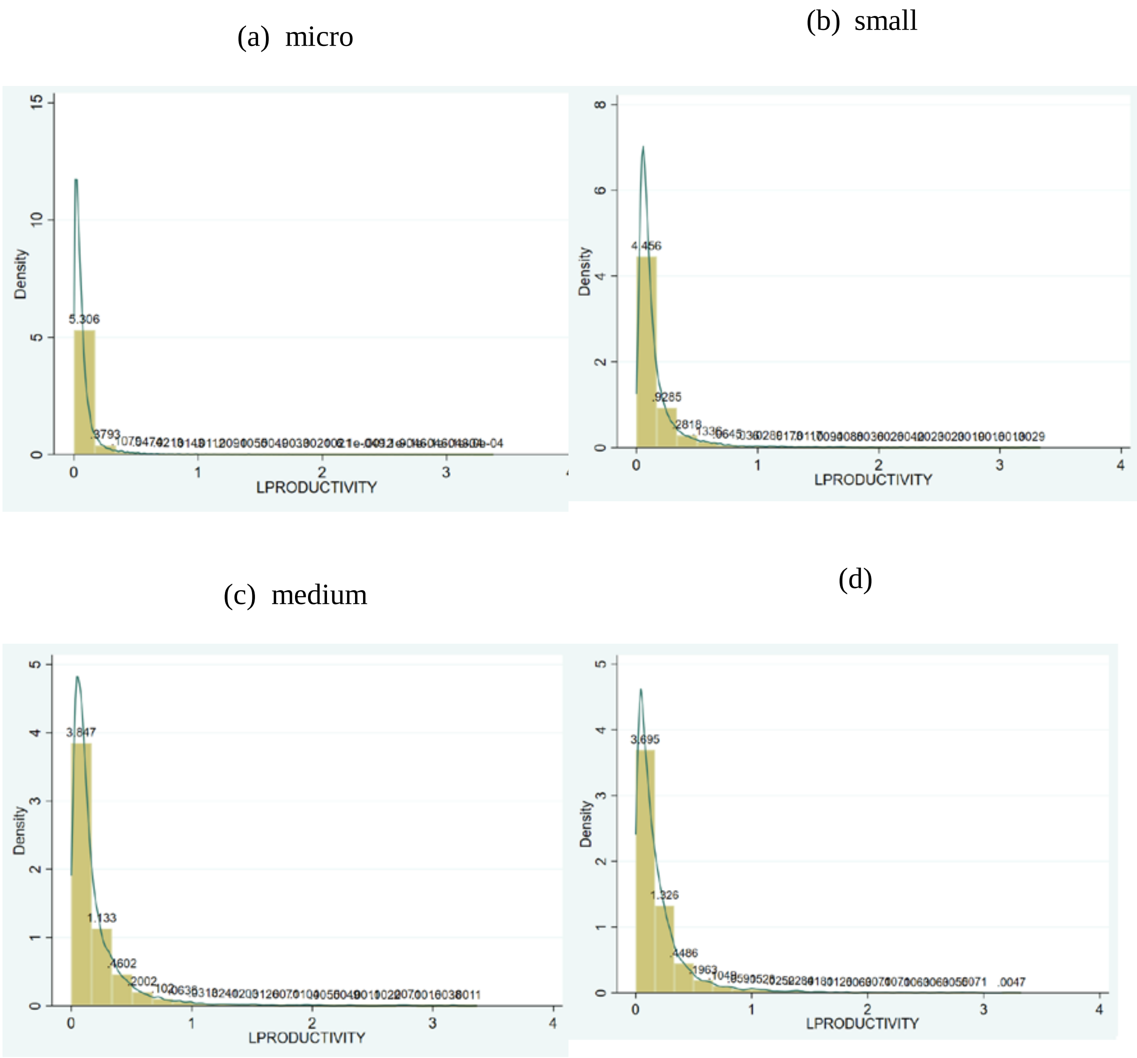
shows a level of productivity higher than 1. In fact, this distribution is close to other datasets, with the ratio of productivity in the top and bottom $$ percentiles being close to 2 (Syverson, 2011).

Figure 1. Distribution of productivity.



As in other studies, larger firms have a higher average productivity level. While the average revenue per employee of micro firms is just 87,000 euros, that number increases to 162,000; 205,000; and 217,000 euros for small, medium, and large firms respectively. This is reasonable according to the existing literature in the field, where size is usually considered as a source of firm's performance disparities. The reason is related to the increased capability of larger firms to cope with sunk costs more easily, present more capacity for diversifying risks, and face lower financial restrictions (Acs and Audretsch, 1988; Cohen and Klepper, 1996). This means that bigger firms are usually expected to be more productive than smaller ones. The distribution of productivity itself is not very different across the size of firms. Figure 2 shows that most firms display low productivity with just a few top performers reaching high levels of productivity.

Figure 2. Productivity distribution by firm size.



Important differences in productivity arise between economic sectors as highlighted in Table 4. The most productive industry is wholesale commerce, and the least is the lodging industry, with a five fold level on average. Within each sector, typically the larger firms are the more productive. Similar differences exist across sectors and are fully in line with observations on productivity differences in other countries (Syverson, 2011). Note as well that the differences across sectors are much less outspoken than the differences across firms of a similar size.

Table 4. Baseline productivity stats for database, per size and sector.

Sector (CNAE)	*all*	*micro*	*small*	*medium*	*large*
10 Commerce	0.171	0.075	0.177	0.274	0.346
19 Chemistry	0.277	n.a	0.203	0.303	0.376
24 Metallurgy	0.228	n.a	0.153	0.264	0.350
26 IT	0.193	n.a	0.133	0.201	0.264
35 Utilities	0.227	0.094	0.221	0.245	0.344
41 Construction	0.107	0.070	0.119	0.151	0.203
45 Car sales	0.224	0.093	0.268	0.421	0.543
46 Retail (large)	0.301	0.211	0.330	0.337	0.398
47 Retail (small)	0.128	0.099	0.171	0.159	0.169
49 Transport	0.116	0.069	0.130	0.151	0.172
55 Lodging	0.066	0.042	0.075	0.074	0.082
58 Info/comunication	0.108	0.070	0.098	0.121	0.185
68 Real Estate	0.078	0.058	0.133	0.219	0.230
69 Services	0.121	n.a	0.104	0.141	0.126
77 Administration	0.084	0.078	0.081	0.116	0.062

C. Hypothesis

Diffusion models of innovation have a few particular predictions we can test. In the model of endogenous innovation diffusion across firm by Benhabib et al. (2021) the distribution of productivity is pinned down by the innovating behavior of firms. Some adopt new technologies, while others invest in new inventions. What keeps together the productivity distribution in equilibrium are two countervailing forces: while ‘creative’ firms could continue investing in new products or processes, the cost of inventing and the eventual adoption by less productive firms constrain this incentive.

As a result, in equilibrium, lower-productivity firms invest in adopting technologies but as firms get closer to the frontier, this effect gets less pronounced, and medium firms will invest less in adoption but more in innovation; while the highly productive ‘creative’ firms invest a lot in innovation.

Technologies that are easy to adopt, either because they have a low cost or a high likelihood of being adopted, would compress the productivity distribution as less productive firms catch up with the leaders. Leaders hence drag productivity levels – and hence spur economic growth – by innovating more, yet their incentives to innovate are limited by the cost of innovation and the ease with which laggards may catch up. Costly innovation and easy adoption may curb productivity growth as more firms' free ride on innovation efforts by the leaders in each sector.

We therefore expect productivity to have a negative impact on technology adoption. As the adoption is easy and not too costly, laggard firms try to catch up with the leading firms in the sector, while leaders themselves may be pushed to reduce innovation and hence experience less productivity growth.

This effect should therefore also be conditional on size, i.e. larger firms may not experience stronger incentives to adopt technology, while for small firms it is a way to catch up with the large players and grow quickly.

Sectoral effects should play a role in technology adoption only to the extent that a spexific technology is enabling firms to grow. We do not expect the effects of productivity on innovation to differ actually, since the same 'innovation and adoption' mechanism may be at work, but we might observe relevant differences in intensity of the effect, as some are more prone to quick changes to online sales (retail, travel) than others (utilities, …).

D. Methods

In order to test whether productivity or firm size matter for the adoption of innovation, we can test a basic probit model, as in (1):

(1) $$p_i = \alpha_i + \beta q_i + \rho X_i + \theta D_i + \varepsilon_{i,}$$

where p_i is the probability of adopting ecommerce, q_i measures productivity, X_{it} is a vector of control variables, and D_i dummy variables for different sectors or firm size, and ε_i the error term. In order to analyze how adoption vary with some characteristics of the firms, we must take into account the potential selection bias in firms starting online sales. The sample of firms is not entirely random – in particular one can expect that firms with lower (potential) sales are more likely not to invest in technology – leading to a sample selection problem. Only those firms that actually have an interest in moving to online sales are likely to take steps to invest in this technology.

Hence, we select only those observations for which the firm has started to use a website, and select only those firms with an online presence. In this case, we test (2) with the heckman probit procedure, substituting productivity with a proxy derived from a prediction of the use of a website. We include as drivers for the use of a web page overall ICT expenditures on equipment, personnel and training (also available in the database).

(2) $$p_i = \alpha_i + \beta \hat{q}_i + \rho X_i + \theta D_i + \varepsilon_{i,}$$

We report the estimates of the of this heckman probit, together with the number of selected firms (on the total), and the correlation coefficient between the error terms of (2) and the selection equation. We test if the errors are uncorrelated to check if we can ignore the selection equation.

We report the baseline result for (2), and then also extend the result for different levels of productivity to check for catch up in technology adoption in line with Benhabib et al. (2021). We provide several robustness checks on these assumptions, first by looking into firm size or the sectoral composition. We then also subject the test of the diffusion model to other checks, in particular different types of technologies.

III. Results

A. Baseline

The full sample result in Table 5a indicate on this sample of 52,810 firms that productivity has a negative effect on the probability of starting e-commerce, however, the impact is small and not significant. Table 5b further shows that the selection equation based on the use of a website, is in a significant way explained by different ICT expenses, as spending on personnel, training and equipment are all significant drivers. The heckman probit results further show that the selection coefficient (0.11) is not high, but is significant and indicates that the choice of starting a website is indeed relevant for the choice of starting ecommerce. These baseline results are also robust to heteroskedasticity.[3]

Table 5. Heckman probit results for full sample.

	(a) Heckman probit model		(b) selection equation	
n (selected)	52,810	(34,638)	ICT experts	1.02 (0.02)
β (s.e./p-value)	-0.0111	(0.0063 /1.77)	ICT training	0.55 (0.05)
ρ (p-value)	-0.11	(0.00)	ICT training per workers	0.08 (0.04)
			ICT spending per worker	6.56 (3.69)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

[3] The result holds with a similar coefficient, and is still significant at 1%, even if we correct for heteroskedasticity and cluster per sector (-0.01, s.e. 0.079), or firm size (-0.01, s.e. 0.045).

To examine now if firms catch up by adopting technologies, we split the sample into high and low productive firms, taking different thresholds. We first split the sample in a top 5% group and compare the result to the bottom 95%. In this case, the heckman probit results in Table 6 (columns and c) shows us that the impact of productivity on e-commerce is positive, and not significant for the leader firms, as expected. For the less productive firms there is catch up going on, but the negative effect of productivity on innovation is as limited as for the top firms, and not significant.

Table 6. Heckman probit for laggards and leaders.

	(a) Laggards (bottom 95%)	**(b) Laggards (50- 95%)**	**(c) Leaders (top 5%)**	**(d) Leaders (top 1%)**
n (selected)	50,025 (32,324)	24,745 (18,650)	2,785 (2,314)	555 (460)
β (s.e./p-value)	-0.01 (0.00 / 0.14)	-0.08 (0.02 / 0.00)	-0.0141 (0.05 / 0.81)	-0.27 (0.20 / 0.17)
ρ (p-value)	-0.08 (0.00)	-0.25 (0.00)	-0.57 (0.00)	-0.81 (0.00)

Note: number of firms in sample, and selected firms; coefficient and standard error plus p-value of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

As Figures 1 and 2 show, a large majority of firms have actually very low levels of productivity, and these firms might be outliers. Hence, we repeat the same model on a sample of medium productivity firms that find themselves in the top half of the sample in terms of productivity, but not in the top 5% (Table 6, column b). In this case, the effect is stronger and significant, indicating these firms are catching up fast to the top firms in terms of technology, while the leaders have indeed slowed down (column c).

We also tried a sample another sample split, by limiting the focus on the top 1% firms with very high productivity (Table 6, column d). In this case, the leaders again do not display a significantly different behavior, indicating they are not running away from the rest of firms in this particular technology. As the number of observations is rather limited, the results should be interpreted with caution.

B. Size matters

Another way to see that firms are catching up is to see whether smaller firms significantly raise their adoption, in spite of their lower productivity. Table 7 shows that firm size is indeed affecting the result. In fact, we observe that the effect gets significantly weaker as we move to larger firms, which is consistent with a shift in the distribution where smaller laggard firms catch up by adopting innovation with the larger leaders, yet the largest firms do invest in technology as well.

The combined results of Table 6 and 7 seem to indicate that intermediately productive firms catch up with the leaders, and that these most productive leaders do not innovate much, but that this is not necessarily correlated with firm size. Very small firms (entrants) catch up quickly and large firms (incumbents) invest in innovation as well, but small and medium sized enterprises do not do so. Entrants and large incumbents move up the productivity ladder, while the small and medium sized firms lag behind. This might indicate that innovation is not too costly, and is easily spread, at least to incumbents.

Table 7. Heckman probit results per size.

	micro	**small**	**medium**	**large**
n (selected)	16,211 (4,982)	18,213 (12,994)	10,771 (9,420)	7,615 (7,242)
β (s.e./p-value)	-0.13 (0.02/0.00)	-0.03 (0.01/0.00)	0.00 (0.01 / 0.83)	0.12 (0.01 / 0.00)
ρ (p-value)	-0.11 (0.14)	-0.43 (0.00)	-0.02 (0.82)	-0.53 (0.03)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

C. Catch up per sector

The catch up should be similar across sectors, but the intensity of the impact will differ depending on the size of firms, their level of productivity and the adaptability of the sector to this particular innovation. The difference in intensity of the effect is actually quite striking in Table 8. There is catch up in each sector, except for a couple of sectors.

The most striking result is the one of for lodging and administrative services, both of which have the lowest productivity levels, as could be seen in Table 4. For administrative services, the largest companies even have the lowest levels of productivity. This likely makes all firms more or less evenly adopt ecommerce, and results in a positive significant coefficient for all firms in this sector.

Another sector with a positive effect of productivity is the IT sector or the tech and communication sector, but this is perhaps no surprise given the nature of the industry. Finally, there is a positive – but insignificant – effect in the utilities sector. This might be driven by the particular nature of the sector, with a few large firms dominating the sector.

Table 8. Baseline ecommerce stats for database, per size and sector.

Sector (CNAE)	*(a) all*	*no. selected firms*	*(b) lag*	*(c) lead*
10 Commerce	-0.11*** $	4,826 (3,033)	-0.14***	-0.28
19 Chemistry	-0.03 $	1,903 (1,696)	-0.04 $	-0.20 $
24 Metallurgy	-0.11** $	1,779 (1,537	-0.08* $	0.30
26 IT	0.14***	2,829 (2,464)	0.16**	-0.29 $
35 Utilities	0.07 $	1,483 (1,080)	-0.02 $	-
41 Construction	-0.23* $***	5,146 (2,588)	-0.24***	-0.08 $
45 Car sales	-	-	-	-0.24
46 Retail (large)	-0.02 $	5,083 (3,331)	-0.04 $	0.39* $
47 Retail (small)	-0.02 $	5,194 (2,426)	0.01 $	0.04 $
49 Transport	-0.14*** $	4,311 (2,224)	-0.15*** $	-0.09 $
55 Lodging	0.27*** $	2,701 (2,385)	0.26*** $	1.10
58 Info/comunication	0.17***	3,280 (2,627)	0.15*** $	-
68 Real Estate	-0.05* $	3,576 (1,480)	-0.04 $	-0.24
69 Services	-0.07*** $	2,890 (2,558)	-0.04 $	-0.46* $
77 Administration	0.27***	5,009 (3,539)	0.21*** $	0.46***

Note: number of selected firms; coefficient and significance of the effect of log productivity on adoption probability of technology (* is at 10%, ** at 5%, and *** at 1%); $ indicates significance of Chi2 test for ρ=0)

These insights are confirmed if we look at low and high productivity firms in each sector. Leaders do not actually invest in technology adoption, except for administrative services, while in most sectors the laggards experience a negative impact. Again, these numbers should be interpreted with caution given the sometimes limited number of firms in the top productivity category.

D. Robustness checks

D1. Explaining e-commerce

So far, we have modeled e-commerce as a binary choice, yet multichannel companies that offer both online and offline transactions might have grown in importance (REF). Some firms are not purely online or offline, but provide a mix of online sales. One way to model this choice is to take different percentages and cut-off values for different levels of e-commerce. We do so by ordering firms in three groups: those with less than 5% sales, those with more than 90% sales and all the intermediate firms in a separate group.

An ordered Hackman probit model indicates very similar findings as in the baseline model. Table 9 shows that a rise in productivity reduces by 0.07 the probability of starting ecommerce. The selection variables in the first stage regression are still significant, and the selection coefficient is low at -0.10 (yet stays very significantly different from zero).

Table 9. Heckman ordered probit for ecommerce adoption.

	All firms
n (selected)	52,810 (34,638)
$\boldsymbol{\beta}$ **(s.e./p-value)**	-0,07 (0.01 / 0.00)
$\boldsymbol{\rho}$ **(p-value)**	-0.10 (0.00)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

D2. Alternative technologies

A potential criticism on the results above is that ecommerce adoption is just one particular technology, and that firms might behave very differently when faced with another type of innovation. The INE survey luckily provides us with alternative IT innovations that Spanish firms implement. One such innovation is the use of Internet to make purchases for the firm. This is expected to facilitate the internal purchasing departments to find out better offers and prices, as well as reducing time and intermediation costs, and hence has potentially a strong impact.

We repeat the same procedure as before but substitute ecommerce with online purchases. In this case, the binary indicator is chosen to be 1 at a cutoff value of 90% (i.e., an amount of less than 10% online purchases is considered to be an offline firm). We report the same baseline estimates, for the full sample, and a sample of leaders (in the top 5% of productivity) and laggards (in the bottom 95%). In this case, overall, more productive firms are less likely to adopt the technology, and we find that leaders are significantly less likely to adopt online purchase tools, while laggard firms are likely to adopt the technology.

A similar phenomenon occurs for Internet of Things. Firms specializing in this sector overall are more likely to adopt this technology (column a, panel II, Table 10), but this is mostly the case for the least productive firms. As column c of panel B shows, there is no adoption in the leading firms, while the less productive firms do adopt.

For cloud computing, the situation is reversed (panel III, Table 10). While more productive firms adopt this technique, it is most outspoken for the leading firms. The effect is in fact about eight times as strong as for the laggards. This might be the consequence of cloud computing being concentrated still in a few large firms that move data handling to large servers. The volume of data handled by these firms is already managed with high-tech, hence cloud computing is mostly reserved for productive companies.

Finally, investment in Big Data solutions is on average adopted by more productive firms, but this is not particularly significant for the leading firms, but neither is this the case for the laggards. Adoption of Big Data solutions is not widespread in firms (just 6% of the sample).

Table 10. Heckman probit for online purchases.

	(a) All	(b) Laggards (bottom 95%)	(c) Leaders (top 5%)
	I. Online purchases		
n (selected)	52,810 (34,638)	50,025 (32,324)	2,785 (2,314)
β (s.e./p-value)	-0.03 (0.00 / 0.00)	-0.01 (0.00 / 0.08)	-0.11 (0.05 / 0.04)
ρ (p-value)	-0.66 (0.00)	-0.66 (0.00)	-0.84 (0.00)
	II Internet of Things		
n (selected)	40,882 (22,710)	38,936 (21,235)	1,110 (833)
β (s.e./p-value)	0.07 (0.01 / 0.00)	-0.07 (0.01 / 0.00)	-0.00 (0.10 / 0.98)
ρ (p-value)	0.62 (0.00)	-0.73 (0.00)	-0.76 (0.00)
	III Cloud Computing		
n (selected)	52,810 (34,638)	51,240 (33,341)	1,570 (1,297)
β (s.e./p-value)	0.04 (0.01 / 0.00)	0.04 (0.00 / 0.00)	0.33 (0.08 / 0.00)
ρ (p-value)	-0.99 (0.00)	-0.99 (0.00)	-0.99 (0.00)
	IV Big Data		
n (selected)	52,810 (34,638)	51,133 (33,246)	1,677 (1,392)
β (s.e./p-value)	0.02 (0.01 / 0.00)	0.00 (0.01 / 0.81)	0.08 (0.08 / 0.29)
ρ (p-value)	-0.82 (0.00)	-0.82 (0.00)	-0.91 (0.00)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

D3. Selection variable

In order to select companies that start e-commerce, we chose to select those firms that had at least a website, but this might seem a too obvious choice, as it is a requirement for selling online, or also because having even a simple website might nowadays seem obvious for most businesses.[4] Hence, an alternative selection variable might be the expenses on ICT in a company. We use ICT spending and ICT training (per worker), and find a very similar result again, with an impact of -0.18.

Table 11. Heckman probit for ecommerce adoption, using ICT expenses for selection.

	all
n (selected)	56,438 (37,909)
$\boldsymbol{\beta}$ **(s.e./p-value)**	0.01 (0.00 / 0.00)
$\boldsymbol{\rho}$ **(p-value)**	-0.34 (0.00)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

D4. B2C or B2B

E-commerce is not just a service to final customers, it is likely even more important for B2B. The INE survey allows distinguishing firms into those that sell B2B or B2C. While the effect is negative and of a similar size for B2C firms, it is significantly stronger and significant anymore for the B2B firms (Table 12), showing the relevance of technology adoption when specializing in services to other businesses.

Table 12. Heckman probit for B2C and B2B.

	B2B	**B2C**
n (selected)	44,742 (26,899)	52,810 (34,638)
$\boldsymbol{\beta}$ **(s.e./p-value)**	0,11 (0.01 / 0.00)	-0.0111 (0.0063 /1.77)
$\boldsymbol{\rho}$ **(p-value)**	-0.35 (0.00)	-0.11 (0.00)

Note: number of firms in sample, and selected firms; coefficient and standard error of the effect of log productivity on adoption probability of technology; and correlation of equations (and p-value of a Chi2 test for ρ=0)

[4] Nevertheless, just 22% of Spanish firms actually have a website.

IV. Conclusion

The literature on endogenous technological change allows modelling firm specific incentives to innovate, and examine (the distribution of) productivity at firm level, as well as the overall economic growth rate.

This paper tests different proposition of the Schumpeterian endogenous growth literature by examining a specific technological innovation – ecommerce – on a large dataset of Spanish firms between 2017-19. We take into account the incentives to adopt technologies with a heckman probit model. The main finding is that laggard firms do try to catch up by investing more in new technologies, in spite of starting at lower productivity levels. This strongly depends, however, on the type of sector, and on the particular type of technology, as well as the specialization in B2B or B2C.

Our results have an important bearing on the development of endogenous growth models of technology diffusion, as it falsifies some channels that push firms to innovate or not. Our results also have important implications for policymakers' stance towards ICT. Widespread subsidies for the adoption of online technologies to make 'firms go online' might actually backfire by reducing incentives to innovate by the sectors' leaders, thereby curbing economic growth.

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