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Assessing e-commerce productivity for French micro firms using Propensity Score Matching

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Abstract
The benefits of e-commerce are apparent not only for small and medium enterprises (SMEs) and large firms, but also for micro firms. Hence, implementing e-sales for micro firms is worth exploring. This study examines the relationship between the use of e-commerce and productivity implications on micro firms in France using Propensity Score Matching (PSM) for the year 2012. Data used in the analysis is based on community survey "ICT & e-commerce" for micro firms. The main objective of using PSM is to assess productivity between, on the one hand, e-selling micro firms and, on the other hand, the non e-selling micro firms. The empirical results show that e-selling micro firms are more productive and have a higher turnover in 2012.

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Keywords ICT; E-commerce; micro firms; productivity; Propensity Score Matching

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1 Introduction

The benefits of e-commerce are apparent not only for large firms but also for small and medium enterprises (SMEs) (Grandon and Pearson, 2004) and micro firms. Deciding whether to implement B2C is difficult in many organizations and particularly in micro firms. This vital decision may either promote growth in an organization or lead to its downfall; consequently, all aspects of implementation must be considered before reaching a consensus within an organization.

Scarce studies have investigated the magnitude of all these factors on B2C e-commerce implementation in micro firms. Thus, elucidating the factors required for successful electronic commerce, particularly in the micro firms, is a worthwhile endeavor.

Most research on the e-business activities of SMEs had focused on SMEs in general but very little has been published specifically about the behavior of micro-enterprises. Moreover, much of the research on SMEs' use of e-commerce focused on adoption patterns and barriers to adoption rather than on business outcomes. Based on this theoretical foundation, we strive to describe and analyze micro-enterprises' patterns of use and value creation with Internet technologies and e-business solutions. Almost all researchers studying the technological behavior of micro-enterprises have used qualitative approach. The current research seeks to fill this void in by offering a first attempt to understand the impact of e-commerce on micro firms' productivity throughout quantitative data. More precisely, we aim to complement the accomplished work by using data from the first version of survey on micro firms' e-commerce in France called TIC-TPE 2012[1]. The main objective of this study is to enrich the literature and to provide a framework to analyze e-commerce performance of micro firms in France, and to assess profitability for e-selling and non e-selling micro firms using propensity score matching.

To undertake the study, we examine the relationship between the use of e-commerce and productivity implications on France' micro firms. In this sense, an econometric study is conducted using data collected from the National Institute of Statistics and Economic Studies in France (INSEE) of the Information and Communication Technologies Survey.

[1]The slowness and complexity of the procedure to have access to confidential databases, have limited the scope of our research for the year 2012, the year of launching the first survey.

This study is structured as follows. It starts with a brief literature review in which impacts of e-commerce on productivity and e-commerce adoption by micro French firms are discussed. Data and descriptive statistics section then follow. Next, the empirical model is presented. Finally, the results are discussed.

2 Literature review

2.1 E-commerce and productivity

Over two centuries, the concept of "productivity" has been investigated by researchers in different disciplines. Quesnay (1766) was the pioneer in studying the concept and since that time it has been applied to multiple situations in different levels in relation to economic systems. According to the literature, productivity represents one of the main basic variables governing economic production activities (Singh et al., 2000; Gordon and Gordon, 2000; Kiani and Ahmed, 2013).

The effects of ICT on performance, demand for skills, and ultimately on productivity, have been the source of much research (Black and Lynch, 2001, 2004; Kretschmer, 2012; Cardona et al., 2013; Bloom et al., 2014; Chun, 2003).

Nowadays, ICTs and mainly e-commerce, are becoming necessary for firms in their economies and development (Barnes and Hunt, 2013; Chiu et al., 2013; Kiani and Ahmed, 2013). In terms of productivity, anterior studies confirm that ICT has two productivity effects: a direct effect, as an input of the production process, and an indirect impact through the way in which they streamline the underlying organization of business process. A lot of focus has been given to the direct productivity impact of information and communications technology capital (Stiroh, 2002; Zwick, 2003; Cecchini and Scott, 2003; Bloom et al., 2014), with growing success as the subtleties of time and heterogeneity are taken into account (O'Mahony and Vecchi, 2005). On the other hand, attention is now turning to the indirect effect that ICT is having on the conduct of business (Black and Lynch, 2004; Beynon-Davies, 2013) and to the use of e-commerce (Matthews et al., 2001).

Research launched in the 1980s and 1990s did not prove evidence that support a positive link between IT investment and firm-level productivity (Dedrick et al., 2003). However, since 1995 a body of literature started to appear that highlights the positive influence of e-commerce on productivity and economic growth of firms (Allcock et al., 2002; Brynjolfsson and Hitt, 2000; Clayton and Criscuolo, 2002). First, according to these authors, e-commerce could be used as a tool to improve the efficiency of research and development. Second, e-commerce is vital in improving commercial communication through access to various big markets. Finally, e-commerce plays an important role in growing the effectiveness and efficiency of business processes. In addition, e-commerce may expand the customer base and generate a higher quantity of sales and consequently higher productivity (Chang et al., 2003). Previous literature also indicates that e-commerce can allow enterprises to access wider markets and to expand the customer base (Gunasekaran et al., 2002). For Fruhling and Digman (2000), e-commerce has significant effects on each of the business-level strategic areas. Actually, by cutting costs, growing efficiency, and reducing time and distance, e-commerce is an important tool to increase productivity. E-commerce has a huge effect on improving the local productivity and prosperity in a country. It encourages economic growth, breaks down barriers for market entry and allows firms to compete in an international level (Wymer and Regan, 2005).

In the UK, the results of a study conducted by Criscuolo and Waldro (2003) showed that buying online positively impacts labor and total factor productivity, while selling online has a negative effect on productivity. In addition, Motohashi (2007) highlighted the positive effect of e-commerce on productivity in Japan, and Atrostic et al. (2004) explored significant impact of e-commerce and computer networks on productivity in the US manufacturing sector.

2.2 E-commerce and micro firms

The European Commission (2005) defines a micro firm as "*an enterprise which employs fewer than 10 persons and whose annual turnover does not exceed 2 million Euro*".

Literature highlights that micro firms use e-commerce in order to develop new sales channels and to gain business benefits that go beyond improving processes (Daniel et al., 2002).

The effects of e-commerce on micro firms could be even stronger than that on large firms because the scope for reducing inefficiencies and increasing productivity is much larger in the micro firms (Poon and Swatman, 1999). Researchers confirm that e-commerce can provide various potential and actual benefits to micro firms (Poon and Swatman, 1999; Dedhia, 2001; Taylor and Murphy, 2004). They can create an international presence using websites for comparatively very little costs (McCole and Ramsey, 2005). In addition, the boundaries of business on the web are not defined by local boundaries, but rather by the coverage of e-commerce, which offers widened access to markets. Therefore, it seems that e-commerce becomes critical for business growth, especially for micro retailers (Laudon et al., 2007).

Starting 2000's, French micro firms have begun to recognize the importance of e-commerce and understand that its adoption could enhance the growth for their business. E-commerce has offered several opportunities for these French firms to penetrate new markets or even to communicate with global suppliers and distributors (Brousseau, 2000). In addition, e-commerce has allowed micro firms to improve the flow of information, to improve availability, to develop market transparency (Jeffcoate et al., 2002), and to decrease errors in information processing (Ng et al., 1998). However, many micro French firms were reluctant in preceding years to adopt e-commerce (Brousseau, 2003). This is due to the lack of strategic direction to computer networks, lack of knowledge and skills or concerns about the costs associated with the introduction of e-commerce (Bélanger and Carter, 2008; Lautre, 2013).

Falk and Hagsten (2015) empirically tested the impact of e-sales activities on labor productivity growth using a sample of micro-aggregated and linked firm-level data covering 14 European countries for the period 2002-2010. They concluded that e-sales activities and labor productivity growth are significantly and positively related when controlling for industry, time, and country effects.

Moreover, according to a study conducted in 2015 by the Federation of e-commerce and distance selling in France, the sector of e-commerce continues to grow and offers opportunities for growth to micro French firms. The number of online shops also continues to increase. The competitive nature of business requires that micro French firms develop and maintain any possible competitive advantage. Increasingly this requires the adoption of e-commerce in few years to come.

3 Data and descriptive statistics

Data used in the analysis is based on Information and Communication Technologies Survey (ICT and e-commerce) for micro firms. The fact that this survey was conducted for the first time for micro firms in 2012 grants us the privilege to work on a database that has never been exploited before. The survey is divided into five modules and each module provides specific information as it is shown in the following list:

- Module 1: The use of computers and related networks
- Module 2: Internet access
- Module 3: Electronic Data Interchange
- Module 4: E-commerce
- Module 5: Companies' information

This survey is partially similar to SME's and large firms, yet with a smaller number of variables/modules.

3.1 Micro firms' adoption of e-commerce

Table 1 displays the results related to ICT and e-commerce adoption by micro firms. Based on a sample of 5102 firms, we can note that 77% of companies own computers, and the percentage of enterprises having Internet access is 73%. In this survey only 27% of firms consider it important to be visible online by having a website.

Concerning electronic sales (e-sales), 18% of the enterprises in our sample conducted sales via a website during 2012, and 21% of the enterprises ordered online with an average amount of 6000 euros per year. In addition, firms realized 30% of their total turnover from e-commerce during 2012, consisting of orders from a website.

Period: 2012	
Number of observations (firms)	5102 firms
Firms with PC	77%
Firms with Internet connection	73%
Firms with website	27 %
Firms that sell online (e-sellers)	18%
Average of e-selling (% of total turnover)	30 %
Firms that buy online (e-buyers)	21 %
Average amount of e-buying	6000€

Table 1: Descriptive statistics, survey:ICT for micro firms-2012

As mentioned above our sample includes 5102 firms for the period 2012. Among them, 320 firms are e-sellers. These firms belong to the following six industries: **a)** Wholesale, retail trade, & repair of motor vehicles and motorcycles **b)** Information & communication **c)** manufacturing industry **d)** professional, scientific & technical activities **e)** accommodation & food service activities **f)** real estate **g)** administrative & support service activities **h)** construction

The percentage of e-selling firms for each industry is listed in table 2. Wholesale, retail trade, & repair of motor vehicles has the highest percentage (28 %) which is followed by Information & communication (20%) and manufacturing industry (19%).

Period: 2012	
Industries	%
Wholesale, retail trade, & repair of motor vehicles	28
Information & communication	20
Manufacturing industry	19
Accommodation & food service activities	14
Administrative & support service activities	9
Professional, scientific & technical activities	5
Real estate	3
Construction	2

Table 2: Percentage of e-selling firms per industry, micro firms, 2012

4 Methodology

The aim of this study is to understand how e-selling events impact micro firms and their productivity outcomes. This question could be answered by looking at the difference between post e-selling event outcomes and traditional selling event outcomes, for the same firm and time period. The problem lies in the fact that both scenarios cannot simultaneously occur within the same firm. Firms that experience an event are likely to exhibit different characteristics to groups of firms that experience no event, therefore direct comparisons between any two groups may suffer from selection bias. Matching can be used to address this problem by identifying a control group of firms with same characteristics that match the event group. The methodology and implementation of these steps are explained below.

We utilize the Propensity Score Matching (henceforth, PSM) in order to assess productivity between, on the one hand, e-selling micro firms and, on the other hand, the non e-selling micro firms. This method allows us to compare the outcome of two identical sets of firms in which one group called the treated group has done online selling and while the other group, called the control group, has not. The matching approach does the following: for every firm in the treatment group a matching firm from the control group needs to be found with very similar characteristics on the observables.

PSM has become a popular approach to estimate causal treatment effects and minimize bias by matching cases to controls based on a set of baseline covariates. It is widely applied in very diverse fields of study health services research, pharmaco-epidemiology and health economics. Rosenbaum and Rubin (1983) were the first to introduce and publish the PSM technique. PSM requires forming matched sets of treated and untreated subjects who share a similar value of the propensity score (Rosenbaum and Rubin, 1983, 1985)

In general, PSM is used when a group of subjects receive a treatment and we would like to compare their outcomes with the outcomes of a control group (that did not receive the treatment). The most popular example of treatment evaluation is when we estimate the effect of a training program on job performance. Then we would have two groups: people who have received the training and people who have not. Then, we would want to evaluate the effect of this training program on job performance.

In our study, the treated group is the one whose firms sell online and the control group is the ones whose firms don't sell online. Moreover, the outcome variable is turnover per employee (

4.1 Propensity Score Matching

In the first step, the observations are assigned into two groups: the treated group that has received the treatment, and the control group that has not. Treatment Z is a binary variable that determines whether or not the observation does online selling. $Z = 1$ for treated observations (firms that sell online) and $Z = 0$ for control observations.

Given a sample of observations and a treatment, each observation has a pair of potential outcomes Y_{i0} and Y_{i1}, the outcomes under the control group and the treated group respectively.

For any arbitrary firm i, the observed value of the outcome variable may be written as:

$$Y_i = Y_{i0}(1 - Z_i) + Y_{i1}Z_i \tag{1}$$

where, $Z_i = 1$ indicates the firm was assigned to "treatment" (i.e. doing online selling) and $Z_i = 0$ indicates assignment to control (i.e. non doing online selling).

For each observation, the average treatment effect (ATE) is defined as: (Imbens, 2004)

$$\tau = E[Y_{i1} - Y_{i0}] \tag{2}$$

The ATE is the average effect at the population level of moving an entire population from untreated to treated. A related measure of treatment effect is the average treatment effect for the treated (ATT) (Imbens, 2004), it's the average effect of treatment on those observations that ultimately received the treatment (in the following we will consider ATT, the parameter of interest in most evaluation studies). The ATT is defined as:

$$\tau_1 = E[Y_{i1} - Y_{i0}|Z = 1] = E[Y_{i1}|Z_i = 1] - E[Y_{i0}|Z_i = 1] \tag{3}$$

Matching methods[2] involve the construction of counterfactual expectations of the dependent variable; that is an estimation of Y_{i1} for the firms which did not sell online the past and an estimation of Y_{i0}) for the firms which sell online .

Such counterfactual means are generated by assigning values of $Y_{i0|Z=1}$ for firms that did online selling and $Y_{i1|Z=0}$ for firms that did not online selling.

These unobserved quantities are estimated by averaging over the observed values of Y for units that are similar on the covariates, but did the opposite. Hence, for each unit there are two potential outcomes, Y_{i0} and Y_{i1}, which may be estimated by:

$$\hat{Y}_{i0} = \begin{cases} Y_{i0}, & \text{if } Z_i = 0, \\ \bar{Y}_{i0(m)} & \text{if } Z_i = 1, \end{cases} \tag{4}$$

and

$$\hat{Y}_{i1} = \begin{cases} \bar{Y}_{i0(m)} & \text{if } Z_i = 0, \\ Y_{i1}, & \text{if } Z_i = 1, \end{cases} \tag{5}$$

where $\bar{Y}_{iz(m)}$ is the mean of the outcome variable for the matched units. Then the matching estimator of the average treatment effect τ has the form

$$\hat{\tau}_m = (n)^{-1} \sum_{i=1}^{n} (\hat{Y}_{i1} - \hat{Y}_{i0}) \tag{6}$$

In this study we use the nearest-neighbor matching [3] (NNM) that takes the closest match from the comparison group in terms of the propensity score for each observation within the treated group (one to one matching).

Second, once we have a matched sample, the treatment effect can be estimated by comparing

[2]It exists several types of matching, i.e: one-to-one matching, k-Nearest neighbors matching, radius matching, kernel matching, local linear regression matching, Spline matching, and Mahalanobis matching. A review on each method can be reviewed in the article of Caliendo and Kopeinig (2008); Stuart (2010)

[3]Nearest neighbor can be conducted with replacement, without replacement and can also be carried out with more than one neighbor being matched to each treated individual (k-nearest neighbors).

outcomes between treated and control firms in the matched sample.

Matching estimates may be derived from comparing mean levels of outcomes across firms that differ in selling online or not, yet share a similar configuration of the pretreatment covariates which determine selection. Groups of firms that share a similar configuration of covariates have roughly the same propensity to sell online, though only the "treatment" group actually did.

Finally, to assess the quality of matching, we perform a covariate imbalance testing to check whether the propensity score adequately balances characteristics between the treatment and control units. Generally, this type of tests can be performed before and after matching to compare the extent of balancing between the two samples before and after having performed matching. More details will be elaborated in the following section.

4.2 Results and discussion

4.2.1 Covariate Imbalance Test before matching

We begin by performing covariate imbalance test before matching in order to have an idea about the specifications and characteristics of each group, respectively treated and control. Reported in Table 3 are the mean of variables for treated and control group. Before matching, e-selling firms (treated group) have a higher number of employees who use computers, greater intangible assets, and liabilities. Also, their turnover and value added are larger than non e-selling firms. They are more productive, they pay higher interest rate. They have higher financial cost and accounts payable.

We note that company's age, number of employees, year of creation, tangible assets, owner's equity, return on investment, and credit rationing are not significant in this test.

One may ask why do firms which rely on e-commerce have higher financial cost? or why is it expensive to succeed? First, the technical side of an e-commerce website impacts the over-all price of the site. It includes all the technical solutions, software, or necessary infrastructure for running the website for the short-medium term in the short to medium term:

- Website hosting,
- online payment system (procurement, storage space,order processing, delivery, etc.),
- commercial management (website synchronization with accounting software, managing suppliers),
- technical maintenance and development of the website.

Second, the marketing side also affects website' price. It includes all marketing ingredients that generate site traffic and improve sales:

- Continuous update of products' catalog, cross-selling and promotional codes,
- e-mailing campaign for customers (preparing and sending newsletters),
- analysis of customers statistics (webanalytics),
- writing a blog,
- comparison shopping engines, etc...

Variables	Mean Treated	Mean Control	% bias	t-test t	t-test p>|t|
Age	12.769	12.956	-1.3	-0.17	0.863
Number of employees	4.46	4.22	10.7	1.39	0.163
Computers' user***	3.522	2.333	59.7	7.73	0.000
Creation'year	1998.2	1998	1.3	0.17	0.863
Intangible Assets (in logs)***	8.622	7.528	25.5	3.09	0.002
Tangible Assets (in logs)	10.992	10.907	5.2	0.67	0.504
Total Liabilities (in logs)***	5.719	5.385	31.7	4	0.000
Owner's Equity	134.36	128.71	1.2	0.23	0.816
Turnover (in logs)***	13.004	12.717	28.1	3.66	0.000
Productivity***	11.63	11.403	26	3.45	0.001
Value added(in logs)**	4.996	4.834	16.5	2.11	0.035
Value added per employee(in logs)*	3.649	3.549	13.5	1.73	0.084
Returns on asset	0.279	0.279	0.0	0.00	0.999
Interest rate***	0.007	0.004	25	3.02	0.003
Credit Rationing	0.178	0.011	10.7	1.20	0.23
Financial costs***	6.262	2.7	18.1	2.93	0.003
Weight of Financial cost1***	0.6	0.075	12.6	3.17	0.002
Weight of Financial cost2	0.0071	0.007	0.1	0.01	0.989
Accounts Payable***	87.565	62.169	17.3	2.74	0.006
Sectoral Dummy Variables					
Ps R^2	0.10	**LR** χ^2	125.21	**P**$>\chi^2$	0.000
* p<0.05	** p<0.01	*** p<0.001			
Ps R^2	0.097				
LR χ^2	121.55				
P$>\chi^2$	0.000				

Table 3: Mean comparison of pre-matching characteristics between treated and untreated

4.2.2 Propensity Score Matching

In the matching procedure, we acquire the propensity score for each firm by estimating the probability of selling online in a Probit model. Since we have multiple variables as outcome, (namely: turnover, productivity[4], and interest rate) we run separately three Probit models for each of the outcomes[5]. Table 4 provides an overview of the Probit estimations. Column (1),(2), and (3)

[4]In this study, productivity is measured by turnover per employee, in logs.

[5]When evaluating multiple outcomes psmatch2 (command used in Stata) reduces to the minimum common number of observations with non-missing values on all outcomes, because otherwise the matching weigths will not sum to the right number. In case of having multiple outcomes with widely differing missing

are the Probit regression for the treatment variable e-selling along the following outcome variables: turnover, productivity, and interest rate respectively.

The parameters of these Probit models are the following: first, Prob>χ^2 is equal to 0.000. Second, Pseudo R^2 is equal to 8.7%. Third, the log-likelihood, which is an indicator of error normality, is equal -587.26. This allows us to conclude that these models are globally significant. The following variables, number of employees and computer users, are significant at 1%, which means that e-selling firms have a greater number of employees and more specifically computer users. The remaining variables, namely, firms' age and its intangible assets do not seem to influence e-selling in a significant way.

Treatment Variable: e-selling			
Covariates	(1)	(2)	(3)
No of employees (in logs)	-0.579***	-0.579***	-0.584***
	(0.000)	(0.000)	(0.000)
Computers' user	0.21***	0.21***	0.21***
	(0.000)	(0.000)	(0.000)
Firm age	-0.003	-0.003	-0.003
	(0.462)	(0.462)	(0.494)
Age squared	0.00003	0.00003	0.00003
	(0.536)	(0.536)	(0.559)
Tangible Assets (in logs)	0.017	0.017	0.015
	(0.553)	(0.553)	(0.589)
Constant	-1.508***	-1.508***	-1.484***
	(0.0000)	(0.000)	(0.000)
Sectoral Dummy Variables			
Nb of observations	2389	2389	2375
Prob>χ^2	0.000	0.000	0.000
Pseudo R^2	0.087	0.087	0.087
Log likelihood	-587.26	-587.26	-587.43
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Table 4: Probit estimations for e-selling micro firms, 2012

After checking the significance of Probit models, we must examine if the outcomes variables are significant in order to confirm our hypothesis. Table 5 presents the estimates of the average

values, we run psmatch2 separately for each of the outcomes treatment effect. It shows, on the one hand, the mean of outcome variables for the unmatched observations for treated and control group (before any matching is done), and on the other hand, the mean of outcome variables for the matched observations.

The "unmatched" results for the outcome variable **turnover** show the difference between the average turnover for treated and control cases, before matching. As we can see, the treated cases in the full sample have a higher turnover than the control cases.

The "ATT", which is the average treatment effect for the treated observations, shows four columns of interest:

- Treated shows the average turnover for the treatment group after matching.
- Controls shows the average turnover for the control group after matching.
- Difference shows the difference between the two.
- T-stat approves that there is statistically significant difference between treated and controls, since its value is significant (equal to or greater than 1.96), hence e-selling micro firms have higher turnover.

The remaining outcome variables share the same explanation with the above. We note that micro e-selling firms have higher productivity (t-stat equal to 2.08), furthermore they tend to have higher interest rate when taking bank loans. And finally, banks limit e-selling firms from taking too many credits even if these firms are willing to pay higher interest rates. Banks consider e-selling firms as risky firms because they worry that e-selling firms may not have the ability to repay the loans back.

Outcome variables	Sample	Treated	Controls	Difference	S.E	T-stat
Turnover(in logs)	Unmatched	13.003	12.717	0.286	0.078	3.66
	ATT	13.003	12.741	0.263	0.115	2.29
Productivity	Unmatched	11.63	11.402	0.228	0.066	3.45
(in logs)	ATT	11.63	11.433	0.196	0.095	2.08
Interest rate	Unmatched	0.007	0.004	0.003	0.001	3.02
	ATT	0.007	0.004	0.003	0.001	2.79
Credit rationing	Unmatched	0.178	0.011	0.166	0.138	1.2
tauxr	ATT	0.178	-0.279	0.457	0.256	1.79

Table 5: ATT for Propensity Score Matching

4.2.3 Covariate Imbalance Test after matching

After matching, we should always check for balance between the two samples before and after having performed matching. In order to do this, we run a Covariate Imbalance Test where we include all the variables used for matching and other variables.

Before going further, we should notice that Covariate Imbalance Test before matching is an unweighted regression on the sample, but after matching the regression is weighted using the matching **weight** variable generated by the software used. And since we ran three Probit regression, we note that we have three weights generated for each outcome variables. Therefore we must run three Covariate Imbalance Test.

Prior to this test, figure 1 demonstrates that the matching was perfectly balanced since both curves are identical.

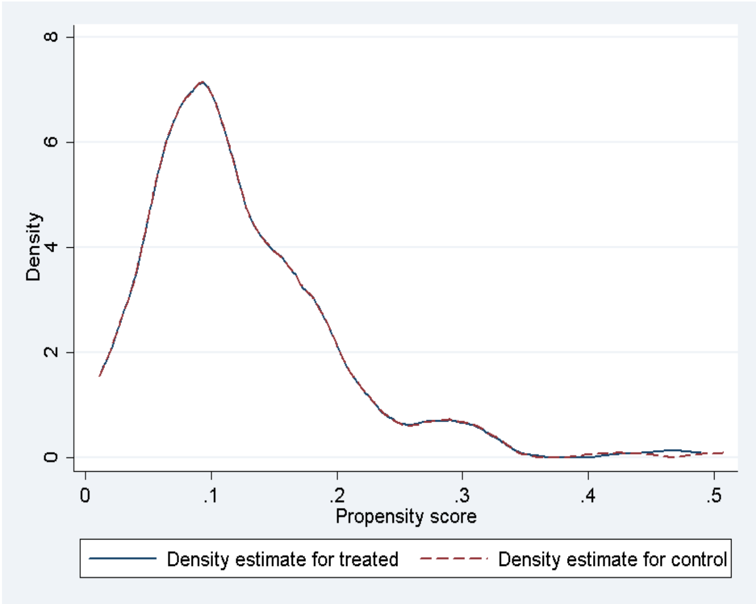

Figure 1: Propensity score densities for treated and control in 2012
Source: Authors' calculation

The quality of the match can be seen in Appendix 6 where Table 6, 7, and 8, show the variables matched on and their relevant test statistics.

The tables show two rows for each variable?unmatched and matched. In each row, it shows the mean of the variable for the treatment and the control group. It also shows the "%bias", which is the standardized bias. Moreover, it shows the "% reduction in bias", which is how much of this bias was eliminated by matching. Negative values for this mean that the bias increased as a result of matching.

To assess balance, we should look first at the t-test to check the statistical significance of each variable, and both the bias and the mean differences between treatment and control in the matched sample.

As can be seen from mean treated and mean control columns of the tables there wasn't quite a large difference between the group of e-selling and those without e-selling before the matching took place, with some of the unmatched p-values showing that the means are statically significant, (intangible assets, turnover, productivity, computer users, finance charge, interest rate, and value added). Regarding the match results, they also show significant difference on some of the variables, namely, intangible assets, turnover, productivity, and interest rate. Thus, both groups (treated and control) do not share the same characteristics. Therefore we can confirm the strength of the match.

We conclude that e-selling micro firms have higher turnover, higher productivity, higher interest rate, higher intangible assets when we take into account the weight of turnover and productivity in the test.

However, when we rely on interest rate weight, intangible assets are always higher for micro e-selling firms and we add to it, interest rate, finance charge, and finance cost .

5 Summary

The rapid pace of technological innovation gives vast/huge opportunities for all kind of firms to create wealth. In this study, we have attempted to contribute to theory by exploring the impact of e-commerce on micro firms. Fundamental research focused on the advantages of e-commerce adoption by medium and large firms, however in this study we focus on micro e-selling firms. We utilize for our analysis a new data set developed by the INSEE for the year 2012 in order to assess productivity. Using the Propensity score matching, we observe that e-selling micro firms are more productive and have a higher turnover.

This study is a step in attempting to understand productivity effect of micro e-selling firms. It raises a number of interesting and challenging paths for future research including an extended longitudinal study of a panel of micro businesses in order to study productivity and profitability impacts across several years. Furthermore, since the productivity effect for e-selling is slightly higher from non e-selling, a detailed study on the reason behind the shift to online business for micro firms is worth exploring.

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6 Appendix

Variables	Unmatched Matched	Mean Treated	Control	% bias	% reduction |bias|	t-test t	p>|t|
Age	U	12.769	12.956	-1.3		-0.17	0.863
	M	12.769	12.269	3.5	-167.6	0.33	0.745
Number of employees	U	4.45	4.22	10.7		1.39	0.163
	M	4.45	4.24	9.5	11.6	0.88	0.381
Creation'year	U	1998.2	1998	1.3		0.17	0.863
	M	1998.2	1998	1.6	-26.5	0.15	0.884
Intangible Assets (in logs)	U	8.62	7.53	25.5		3.09	0.002
	M	8.62	7.83	18.5	27.5	1.75	0.080
Tangible Assets (in logs)	U	10.992	10.907	5.2		0.67	0.504
	M	10.992	11.011	-1.1	77.8	-0.11	0.911
Turnover (in logs)	U	13.004	12.72	28.1		3.66	0.000
	M	13.004	12.75	25	11.2	2.31	0.022
Productivity	U	11.63	11.403	26		3.45	0.001
	M	11.63	11.44	21.8	16.2	2.10	0.036
Returns on asset	U	0.279	0.279	0.0		0.00	0.999
	M	0.279	0.248	4.9	-91589	0.48	0.632
Computer users	U	3.52	2.33	59.7		7.73	0.000
	M	3.52	3.27	12.6	78.9	1.09	0.275
Finance charge	U	6.26	2.7	18.1		2.93	0.003
	M	6.26	3.74	12.9	29.2	1.29	0.200
Interest rate	U	0.007	0.004	25		3.02	0.003
	M	0.007	0.004	25.8	-3.3	2.99	0.003
Finance cost	U	0.007	0.007	0.1		0.01	0.989
	M	0.007	0.003	3.9	-2546	2.06	0.04
Value added	U	4.99	4.83	16.5		2.11	0.035
	M	4.99	4.84	15	9.4	1.36	0.176
Sectoral Dummy Variables							

Table 6: Balancing test for nearest neighbor after matching, weight of turnover

Variables	Unmatched Matched	Mean Treated	Control	% bias	% reduction |bias|	t-test t	p>|t|
Age	U	12.769	12.956	-1.3		-0.17	0.863
	M	12.769	13.039	-1.9	-44.2	-0.17	0.868
Number of employees	U	4.45	4.22	10.7		1.39	0.163
	M	4.45	4.26	8.9	17	0.82	0.411
Creation'year	U	1998.2	1998	1.3		0.17	0.863
	M	1998.2	1998	1.9	-44.2	0.17	0.868
Intangible Assets (in logs)	U	8.62	7.53	25.5		3.09	0.002
	M	8.62	7.83	18.5	27.5	1.75	0.080
Tangible Assets (in logs)	U	10.992	10.907	5.2		0.67	0.504
	M	10.992	11.011	-1.1	77.8	-0.11	0.911
Turnover (in logs)	U	13.004	12.72	28.1		3.66	0.000
	M	13.004	12.75	25	11.2	2.31	0.022
Productivity	U	11.63	11.403	26		3.45	0.001
	M	11.63	11.44	21.8	16.2	2.10	0.036
Returns on asset	U	0.279	0.279	0.0		0.00	0.999
	M	0.279	0.248	4.9	-91589	0.48	0.632
Computer users	U	3.52	2.33	59.7		7.73	0.000
	M	3.52	3.27	12.6	78.9	1.09	0.275
Finance charge	U	6.26	2.7	18.1		2.93	0.003
	M	6.26	3.74	12.9	29.2	1.29	0.200
Interest rate	U	0.007	0.004	25		3.02	0.003
	M	0.007	0.004	25.8	-3.3	2.99	0.003
Finance cost	U	0.007	0.007	0.1		0.01	0.989
	M	0.007	0.003	3.9	-2546	2.06	0.04
Value added	U	4.99	4.83	16.5		2.11	0.035
	M	4.99	4.84	15	9.4	1.36	0.176
Sectoral Dummy Variables							

Table 7: Balancing test for nearest neighbor after matching, weight of productivity

Variables	Unmatched Matched	Mean Treated	Control	% bias	% reduction |bias|	t-test t	p>|t|
Age	U	12.769	12.956	-1.3		-0.17	0.863
	M	12.769	13.907	-7.9	-508.8	-0.66	0.510
Number of employees	U	4.45	4.22	10.7		1.39	0.163
	M	4.45	4.36	4.3	59.4	0.4	0.688
Creation'year	U	1998.2	1998	1.3		0.17	0.863
	M	1998.2	1997.1	7.9	-508.8	0.66	0.510
Intangible Assets (in logs)	U	8.62	7.53	25.5		3.09	0.002
	M	8.62	7.9	16.7	34.6	1.61	0.108
Tangible Assets (in logs)	U	10.992	10.907	5.2		0.67	0.504
	M	10.992	11.063	-4.3	16.7	-0.46	0.643
Turnover (in logs)	U	13.004	12.71	28.1		3.66	0.000
	M	13.004	12.84	16.5	41.4	1.56	0.119
Productivity	U	11.63	11.403	26		3.45	0.001
	M	11.63	11.501	14.8	43	1.45	0.147
Returns on asset	U	0.279	0.279	0.0		0.00	0.999
	M	0.279	0.329	-7.6	-140000	-0.70	0.487
Computer users	U	3.52	2.33	59.7		7.73	0.000
	M	3.52	3.55	-1.4	99.7	-0.12	0.906
Finance charge	U	6.26	2.7	18.1		2.93	0.003
	M	6.26	1.93	22.1	-21.7	2.47	0.014
Interest rate	U	0.007	0.004	25		3.02	0.003
	M	0.007	0.004	25.6	-2.3	2.93	0.004
Finance cost	U	0.007	0.007	0.1		0.01	0.989
	M	0.007	0.0035	4.3	-2860	2.39	0.017
Value added	U	4.99	4.83	16.5		2.11	0.035
	M	4.99	4.89	11.1	33.1	1.01	0.313
Sectoral Dummy Variables							

Table 8: Balancing test for nearest neighbor after matching, weight of interest rate

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