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The effects of cross-border acquisitions on firms' productivity in the EU

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Abstract

This study empirically investigates the extent to which firms in the European Union, once acquired through a cross-border acquisition, show different productivity levels as compared to those firms that have not been acquired. Our identification strategy relies on the combination of Propensity Scores and the Staggered Difference-in-Difference estimator, using firms' balance sheet for the years 2008-2018. We find that cross-border acquisitions decrease the productivity of the acquired firms, especially in the manufacturing sector, both high- and low-tech. We find evidence of origin and sector heterogeneity. Firms targeted by acquirers with ultimate owners originating in emerging market economies and Offshore Financial Centres also decrease productivity of target firms in high-tech manufacturing.

Keywords: Cross-border M&As, TFP, European Union, Propensity Score, DiD.

JEL codes: D24, F23, F60, G34.

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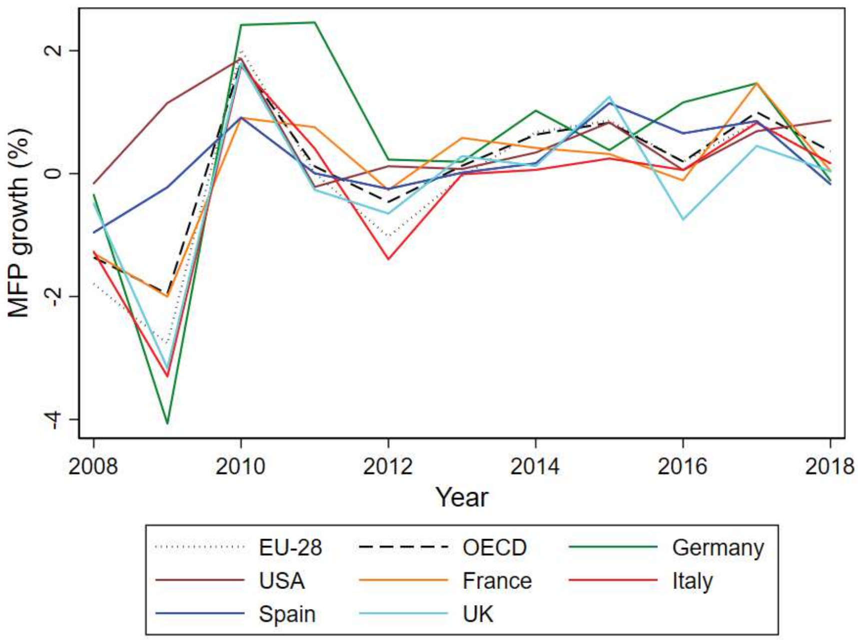
1. Introduction

The persistency of low productivity growth has been well documented in the economics literature and it remains a relevant issue, as it affects citizens' living standards.[1] Since Hansen (1939), the term "secular stagnation" became popular and it was used, at that time, to indicate the crisis faced by the United States in 1938, linked to an insufficient aggregate demand. This term regained popularity over the past decades, and especially after the 2008 financial crisis, when major world economies experienced inadequate aggregate supply linked to a sluggish potential real GDP growth, indirectly lowering net investment and productivity growth (Gordon, 2015). Figure 1 illustrates the annual productivity growth in the European Union (EU) and among OECD countries between 2008 and 2018. While the low productivity issue is common to all of them, in the last years EU countries present an average growth lower than 1%, underperforming the average of OECD countries in most cases. There could be different reasons behind this low productivity growth. For instance, economic sectors and business activities show contrasting levels of productivity, due to factors such as production practices and producers' external operating environments (Syverson, 2011). European geographical regions, with diverse historical development paths, are generally linked to different levels of productivity, also in relation to local availability of production factors (Beugelsdijk et al., 2018). In addition, different economic sectors, such as knowledge intensive ones, could perform differently compared to the overall economy, considering that intangible capital is an important driver of productivity growth (European Commission, 2021). Furthermore, Aghion et al. (2019) argued that statistical agencies might underestimate economic growth, by not being able to correctly disentangle an increase in products' monetary value due to inflation versus real productivity growth, especially in those sectors where new products replace old ones. On top of this, capital inflows could be misallocated toward those firms characterised by a high net worth, but not a high productivity (Gopinath et al., 2017). Finally, a slowdown in the technology diffusion process has also been identified (Andrews et al., 2016). Despite these suggested reasons, improving productivity remains a challenge for policy makers, therefore understanding factors affecting firm level productivity in the EU remains an important research topic.

[1] Lectio magistralis by Mario Draghi, President of the ECB, marking the 100th anniversary of the Deusto Business School, Madrid, 30 November 2016.
See https://www.ecb.europa.eu/press/key/date/2016/html/sp161130_1.en.html.

Figure 1. Multifactor productivity growth



Source: Authors' calculations based on OECD multifactor productivity data.

In addition to the issue of persistent low productivity in Europe, the current political debate often focuses on foreign acquisitions, due to the fear of potential threats for the European sovereignty, in particular when foreign takeovers target firms in strategic sectors. These fears have been exacerbated by the Covid-19 pandemic, and its potential economic consequences. As declared by the President of the European Commission Ursula von der Leyen in March 2020, "*if we want Europe to emerge from this crisis as strong as we entered it, then we must take precautionary measures now. As in any crisis, when our industrial and corporate assets can be under stress, we need to protect our security and economic sovereignty [...]. The EU is and will remain an open market for foreign direct investment. But this openness is not unconditional.*"[2] In this regard, the EU has recently adopted a new Regulation on foreign direct investment (FDI) screening, on the grounds of security and public order, which has been operational since October 2020.

In this context, we perform an analysis of the effects of cross-border acquisitions on target firm productivity, aimed at providing useful insights to feed the political discussion. The main questions we

[2] Press release of the European Commission (March 25, 2020). See: https://trade.ec.europa.eu/doclib/press/index.cfm?id=2124.

intend to address are the following: what happens to target EU[3] companies when they are taken over? Does ex-post productivity of acquired companies differ compared to non-acquired ones? Are there sectoral differences? What are the effects of acquisitions by non-EU investors? To investigate these questions, we perform an empirical study to assess the extent to which cross-border acquisitions in the EU affect target firms' productivity, comparing acquired firms with those companies that have not been acquired. Our identification strategy relies on Propensity Scores and inverse weighting, in order to obtain a comparable control group (i.e. non-acquired firms) and lower potential selection biases, combined with the staggered Difference-in-Difference (DiD) approach recently proposed by Athey and Imbens (2018). We find that during the years 2008-2018 cross-border acquisitions decrease the productivity level of acquired firms, especially in the manufacturing sector.

The contribution of our study to the literature is twofold. Firstly, it adds to the strand of the literature that investigates the relationship between FDI and productivity. Evidence regarding the link between FDI and productivity is rather fragmented and inconclusive, and can be found in the literature in relation to different countries, sectors and time periods. Javorcik (2004) focuses on spillover effects between acquired firms and domestic ones using Lithuanian manufacturing firm-level data. Results showed that there were positive productivity spillovers between foreign affiliates and their local suppliers, in particular in upstream sectors. Using country level data, Alfaro et al. (2009) show that FDI might improve significantly Total Factor Productivity (TFP) of the destination countries when they have well-developed financial markets. Karpaty (2009) investigates the Swedish manufacturing sector, highlighting that foreign acquisitions increase productivity in the acquired companies up to 11%. Schiffbauer et al. (2017) focus on takeovers of UK firms between 1999 and 2007, and show that there was not conclusive evidence of long-run effects of foreign takeovers on TFP at the aggregate level. However, they identified heterogeneity across sectors, and contrasting results in relation to short versus long-term effects. Li and Tanna (2019) look at 51 developing countries over the period 1984-2010, finding a robust direct effect of inward FDI on TFP growth when the roles of human capital and institutions are taken into account. In contrast with previous studies, our analysis provides new evidence of negative effects of inward cross-border acquisitions on TFP of target firms in the European Union. We also uncovered heterogeneity across sectors. In addition to the sectoral dimension, we pay special attention to the potentially differing effects of cross-border acquisitions depending on the country of origin of the acquiring firm, with a special focus on the distinction between technology intensive activities. Some papers have recently explored

[3] Throughout the work, EU means EU27 plus United Kingdom.

productivity differentials between emerging market foreign firms operating in the EU, when compared to developed markets foreign firms, in several sectors. Pittiglio and Reganati (2018) highlight the importance of accounting for the type of FDI and the motivations behind it, as these aspects are likely to affect the performance of foreign owned firms in the EU. Sanfilippo (2015) finds evidence of productivity gaps between emerging and advanced economies foreign owned firms, and concludes that European affiliates owned by parent companies located in foreign emerging economies were less productive. This author also noted that the productivity differentials were larger in more sophisticated manufacturing and services sectors, and when this type of FDI was targeted to Western European countries. Carril-Caccia (2020) studies the case of cross-border M&As in the French manufacturing sector, without finding significant effects on TFP when M&As are carried out by firms originating in developed or in emerging countries. However, this author found an increase in acquired firms' TFP when the M&As is carried out by firms originating in European countries, but only in the long term. We extend this literature by including more countries in our sample, and by using a more granular sector and origin region categorisation.

In addition, the second main contribution of our analysis relates to the strand of the literature which implements Propensity Score Matching (PSM) combined with DiD techniques to study the effects of FDI. In fact, since the seminal papers of Rosenbaum and Rubin (1983) and Heckman et al. (1997), the combination of PSM and DiD has been widely implement in the FDI literature to overcome the issue of selection bias. Girma and Görg (2007) apply this approach to investigate the causal effect of foreign acquisitions on wages of skilled and unskilled workers. In the same vein, Arnold and Javoricik (2009) use this econometric setting to show that in the Indonesian manufacturing sector foreign ownership generates a productivity increase in the acquired plants. More recently, Cushman and De Vita (2017) also used PSM to conclude that developing countries with stable exchange rates attract more FDI relative to those countries with more flexible ones. In relation to the causal effect of FDI on total factor productivity, Schiffbauer et al. (2017) and Carril-Caccia (2020) also rely on the combination of PSM and DiD. Our analysis relies on a similar identification strategy, albeit with two important differences. First, recent critiques have highlighted potential issues of using PSM to improve casual inference in observational data, due to the risk of increasing issues such as imbalance of the distribution of pre-treatment confounders between treated and control units (King and Nielsen, 2019). Because of this, we use inverse probability weighting (based on computed Propensity Scores), instead of PSM, in our DiD model that identifies the effect of the acquisition on target productivity. The robustness of this approach will be extensively tested in section 6. Second, we also exploit the recent contributions made by Athey and Imbens (2018). They develop a methodological setting to estimate DiD models and identify causal treatment effects with multiple treatments occurring at different times, called staggered DiD. Thus, we combine this staggered DiD setting with inverse probability weighting (as well as alternative matching approaches to assess robustness) to identify the causal effect of acquisitions on TFP of target firms.

The remainder of the study is organised as follows. Section 2 illustrates the links between cross-border acquisitions and productivity and section 3 outlines the econometric approach followed. Section 4 describes the dataset and variables. Section 5 discusses the results, while section 6 presents a series of robustness checks. Section 7 concludes.

2. Links between cross-border acquisitions and productivity

Productivity divergence among firms are caused by differences in their ability to combine inputs in order to produce output, meaning that a firm is more productive if it can produce the same output with fewer inputs, or more output with the same inputs (van Biesebroeck, 2008). The combination of inputs is achieved through the firm's production technology. Hence, one of the main ways in which a cross-border acquisition could affect the target firm productivity is through technology transfers (Salis, 2008; Keller, 2004). Firms transfer and acquire new technology and knowledge across borders in several ways, such as trade (i.e. exchanging or purchasing new equipment, intangibles or intermediate goods), exporting activities and FDI (Djankov and Hoekman, 2000). The last form is often viewed as constituting a more fluid and complete form of technology transmission, particularly for intangible assets (such as patent access), since these are often out of reach for firms with a less developed business organization. According to the *internalisation theory,* acquiring firms transfer their intangible assets, such as well-known branding or advanced technological knowledge, to the acquired affiliates abroad (Dunning, 1998; Damioli and Gregori, 2021), which would in turn translate in productivity improvements in the acquired firms due to technical progress post-acquisition. A further way in which a cross-border acquisition can improve the target firm's productivity is through the transfer of superior managerial practices or capabilities (Bertrand and Zitouna, 2008). The successful transfer of these practices would translate into technical efficiency improvement at the firm level, which leads to improved productivity in the target firm. Finally, a cross-border acquisition may also affect firm productivity thanks to economies of scale and scope. Scale efficiency relates to productivity (dis)improvements that arise from (dis)economies of scale. Scale efficiency change typically arise from changes in relative prices or other production incentives (O'Donnell, 2011), such as fiscal incentives. Cross-border acquisitions might decrease average costs or reduce the costs of inputs, leading to higher firm output and economies of scale (Bertrand and Zitouna, 2008). The impact of foreign acquisitions on Returns to Scale (RTS) was directly explored in Girma and Görg (2002), who found that foreign acquired plants were better able to utilise capacity when compared to domestic plants, leading to a reduction of excess capacity in acquired firms. They also found evidence of overall scale adjustments occurring post-acquisition.

Despite these theoretical postulates, empirical literature on this topic has found inconclusive evidence regarding the effects of cross-border acquisitions (for example, positive in Bertrand and Zitouna, 2008, negative in Harris and Robinson, 2002; Girma and Görg, 2002; no or mixed evidence in Salis, 2008; Schiffbauer et al., 2017).[4] Moreover, there are several reasons why a positive impact of a cross-border acquisition on target firm productivity should not be taken for granted. For instance, technology transfers resulting from cross-border acquisitions might not always benefit productivity of the acquired firm through the channels outlined above for several reasons. First, negative effects on productivity can result from a cross-border takeover if it causes dis-synergies (Buckley et al., 2014), which occur when the acquiring and target firms possess stocks of knowledge capital that are not complementary. Moreover, it could also be the case that the technologies are not transferable (Keller, 2004). This might be more prevalent in low-tech manufacturing for example, where intangibles are less prevalent. Second, assuming that technology is transferable, the implementation and utilization of the transferred technology requires that sufficient skills, or appropriate training of the staff, in the newly acquired firm are present (Djankov and Hoekman, 2000; Keller, 2004). Its absence could lead to deficient technology exploitation, which might explain lower TFP post-acquisition. In modern cross-border acquisitions, knowledge intensive assets have become increasingly prevalent. The effective transmission of knowledge intensive assets requires that factors such as skilled labour or suitable infrastructure are present (Dunning, 2009). Therefore, it is likely that for a successful technology transfer, some firm level re-structuring and investment activity post-acquisition would be needed. The extent to which firm level re-structuring post-acquisition is successful might determine a positive or negative effect of a cross-border acquisition on the productivity of the acquired firm. Third, it could be the case that cross-border investors could instead benefit from the transfer of technology and expertise from the acquired firm rather than the other way around (Dunning, 1998; Salis, 2008; Dunning, 2009), particularly in certain sectors. For example, in manufacturing the phenomenon of asset seeking in FDI is rather prevalent, which would result in a reverse flow of assets

[4] Domestic acquisitions are not the topic of this analysis and the discussion of these affects not considered in this review.

from the acquired firm to the acquiring company. This is especially true when the acquiring firm looks for a local target with a better production technology than its own (Salis, 2008). This is also the case with acquisitions where the acquiring firm originates in an emerging economy. In these cases, the theoretical mechanisms that suggest productivity improvements through technology or managerial transfers are less clear (Chari et al., 2012; Buckley et al., 2014; Pittiglio and Reganati, 2018). These types of acquiring firms are more likely to absorb, rather than transfer, technical and marketing knowledge from target firms located in developed countries (Pittiglio and Reganati, 2018; Carril-Caccia, 2020). Buckley et al. (2014) find evidence that acquisitions performed by firms originating in emerging countries are likely to have differing effects on productivity of the acquired company depending on the resources, experience and other characteristics of the acquiring firms. Carril-Caccia (2020) shows that cross-border acquirers from emerging economies did not have a significant effect on TFP of acquired French manufacturing firms.

Further negative cross-border acquisition effects on productivity could be linked to difficulties when incorporating the acquired firm in the structure of the investing company (Harris and Robinson, 2002). An erosion of technical efficiency, and consequently in productivity, of the target company could arise if the internationalisation causes lower coordination or deficiencies in the management control. Moreover, if managerial capacity or competence does not match the requirements of managing a firm in a new market, the acquired firm performance could deteriorate (Balsvik and Haller, 2010; Mattes, 2010). It has also been argued that cross-border takeovers may have a detrimental effect on the target firm performance if the acquiring firm is not well rooted in the local economy and does not have the capability of relocating production among affiliates in different countries (Bandick, 2011). Finally, firms dispersing their production activities across countries because of a cross-border acquisition may also lead to reductions in the benefits of economies of scale (Bertrand and Zitouna, 2008).

The literature has also noted paths in which cross-border acquisitions might affect firm level productivity of non-acquired firms, through changes in competition and market structures in the location or sector of operation of the target firm (Schiffbauer et al., 2017). For example, with imperfect competitive markets, increased market shares by cross-border investors might translate into a share reduction for local firms, which would in turn hinder their exploitation of scale economies (Djankov and Hoekman, 2000). Moreover, increased market concentration might reduce productivity improvement prospects in a given industry (Bertrand and Zitouna, 2008). Indirect effects of FDIs, or spillovers, affecting non-acquired firms have been explored in the literature (Djankov and Hoekman, 2000; Javorcik, 2004; Bruno and Ciloppina, 2017). These typically manifest when non-acquired firms in the same market (or industry) as the acquired firm benefit from learning (for example, through worker mobility) or indirect asset transfer, such as imitation (Girma et al., 2007) or reverse engineering (Djankov and Hoekman, 2000). The arrival of cross-border investors in a given market might generate technological learning externalities for the rest of firms, for example through labour training, increased turnover or the provision of high-quality intermediate inputs (Keller, 2004). Spillovers from cross-border acquirers located in the same industry (horizontal spillovers) are typically found to be weaker (Schiffbauer et al., 2017), when compared with acquirers located up or down the supply chain due to vertical spillovers (Girma et al., 2007). In addition, the type of relation between the cross-border investor and the target firm (such as joint venture and majority acquisition) is also likely to matter in terms of spillover effects (Djankov and Hoekman, 2000; Javorcik, 2004). Some of these factors may indirectly affect the productivity of cross-border acquired firms.

From this review, it is clear that ultimately, differing effects of an acquisition on the productivity of the target firm can occur, depending on factors such as the motives of the acquisition, the sector in which firms operate, or on the country of origin of the acquirer. In the next sections, we investigate the effects of cross-border acquisitions on the productivity of acquired firms in the EU. We also investigate whether there are different effects depending on target firm sector of operation, such as high versus low-tech manufacturing, and to what extent target firm productivity is affected by investors' characteristics, such as originating in developed versus emerging economies or in tax havens jurisdictions.

3. Identification strategy

The objective of this analysis is to identify the effect of cross-border acquisitions on firm level productivity of acquired firms. Therefore, we need an econometric strategy able to identify differences in productivity for the target firm before and after its acquisition, considering as a benchmark those firms never acquired. This set up calls for the panel DiD estimator. In this setting, and in order to identify the causal effects of a treatment, we need to define the treated and control groups, as well as the period in which the treatment is applied. In our framework, the treatment is the cross-border acquisition, and the treated group includes those firms that have been acquired. The control group is composed by firms that have never been acquired. An important feature of our treatment (i.e. the acquisition) is that the period of the treatment is firm specific (i.e. varies between acquired firms), and starts since the year of the acquisition onwards. Due to this feature, we cannot implement a standard DiD, as this approach would imply a treated period common to all acquired firms. Another feature of our treatment is that once the firm is acquired (i.e. treated) it remains treated (i.e. there is no jumping in and out of treatment). Therefore, we rely on the staggered DiD, which allow us to estimate the average treatment effects of multiple treatments (and diverging treated periods) using panel data (Athey and Imbens, 2018).

However, when attempting to attribute a causal effect to the acquisitions, several econometric issues arise in practice, which need to be properly accounted for. First, we are able to observe acquired firms before and after they are acquired, however the counterfactual (the productivity of acquired firms had they not been acquired) is unobservable. This feature makes establishing the proper comparison group to assess the productivity of acquired firms post-acquisition difficult. Second, an issue with endogeneity can arise because cross-border acquirers are likely to have specific motives behind the acquisition of a particular target firm. For example, they could acquire only the most productive firms (McGuckin and Nguyen, 1995), or those firms "on sale", due to sudden negative shocks or facing credit constraints. Therefore, before applying the DiD estimator, we need to define treated and control groups that include firms with similar characteristics, and are therefore comparable. Ignoring these issues could potentially lead to overestimating the impact of the acquisition on productivity (Salis, 2008), with important consequences in terms of the relevant policy conclusions arising from this empirical research.

3.1 Obtaining a comparable control group

In order to overcome the aforementioned biases, before estimating the DiD regression, we estimate the propensity score (PS) for each firm in our sample, which summarises the information contained in a vector of pre-treatment firm controls (Rosenbaum and Rubin, 1983). The PS measures the conditional probability of treatment given the set of pre-treatment control variables. This way, if the conditional independence assumption is satisfied, productivity of the target firms is independent of the acquisition, conditional on the covariates included in the estimation of the PS (Khandker et al., 2010), so the treatment status is random. To obtain the PS, we estimated a logit regression that models the probability of firms being acquired, based on firm characteristics pre-acquisition. The related literature reviewed in section 2 typically used the characteristics of firms on the year immediately pre-acquisition to model this probability. However, based on Chabé-Ferret (2017), we instead use three lags of data pre-acquisition, in order to avoid bias that this author found can potentially affect DiD estimates when conditioning only on one pre-treatment outcome. Chabé-Ferret (2017) suggested that the risk of this bias is diminished when using at least three pre-treatment periods. Afterwards, we use the estimated PS to re-weight the observations in the sample. This way, observations in the control group are weighted to be similar (comparable) to those in the target group. Based on the PS, we compute inverse probability of treatment weights (IPTW). For firms in the target group, the assigned weight is $\omega_{it} = 1/PS_{it}$, while for firms in the control group the assigned weight is calculated as $\omega_{it} = 1/(1 - PS_{it})$. We refer the reader to Robins et al. (2000) for further details on this re-weighting DiD approach.

Despite the approach combining PSM and DiD being rather common in applied literature assessing the links between firm M&As and productivity, PSM has been recently criticised (King and Nielsen, 2019). These authors suggested that PSM is a weak method to improve casual inference in observational data that actually increases issues such as imbalance of the distribution of pre-treatment confounders between treated and control units, model dependence, or bias. These issues originate in the PSM attempt to approximate a completely randomized experiment, rather than a more efficient fully blocked randomized experiment, as it is the case with alternative matching methods. These authors propose that other possible matching techniques, such as Mahalanobis Distance Matching (MDM) (Rubin, 1980) or exact matching (EM) (Iacus et al., 2012). King and Nielsen (2019) however noted that alternative uses of PS, such as inverse weighting, could still be legitimate uses. Therefore, our baseline model, and subsequent granular analysis, is not based on the PSM matched sample, but rather on the re-weighted sample using IPTW. However, we take into account this important criticism and assess the robustness of our estimates to alternative matching procedures, with results shown in section 6.

3.2. Identification of the treatment effect

Besides potential selection bias arising from observable firm characteristics, additional biases might also be caused by time-invariant unobserved firm characteristics. In order to tackle the second set of biases, a panel DiD estimator is used. In this case, we implement inverse weighted staggered DiD, specified as follows:

$$Y_{it} = \alpha_0 + \alpha_1 T_{it} + \boldsymbol{\beta X_{it-1}} + \boldsymbol{\gamma Z_{ct-1}} + \varphi_{\mathrm{i}} + \sigma_t + \epsilon_{it} \quad (1)$$

where Y_{it} is the log of TFP of firm i at time t. T_{it} is the treatment indicator equal to 1 if the firm i is treated at time t and zero otherwise, and α_1 represent the coefficient of interest to detect the DiD effect (Athey and Imbens, 2018).[5] Also included in equation (1) is $\boldsymbol{X_{it-1}}$, which denotes a vector of controls which

[5] Athey and Imbens (2018) extensively discuss a set of assumptions under which α_1 can be interpreted as a weighted average causal effect of the treatment (or more specifically as a weighted average of potential causal comparisons, or of different adoption dates). A key assumption is that the treatment assignment itself is stochastic (i.e. implying

include firm specific characteristics derived from balance sheet data. These variables are selected in order to capture the effects of firm level characteristics that could also be affecting firm level productivity post-acquisition and therefore, eliminate possible confounding effects. Specifically, we include: i) total assets (in logarithms), to control for the size of each firm; ii) total fixed assets over total assets (in logarithms), to proxy the relative importance of fixed, as opposed to intangible, assets for the firm; iii) loans over total assets (in logarithms), to take into account the level of indebtedness; iv) operational costs over turnover (in logarithms), to capture the effects of changes in the production costs per unit of output of the firm; and finally, v) profits over total assets (in logarithms), to include a measure of firm's ability to produce wealth for its shareholders. This ratio also measures firms' returns on assets, which proxies firm economic performance. We also include a vector of macroeconomic factors at the country level ($\boldsymbol{Z_{ct-1}}$) that vary over time, namely inflation and per capita GDP, in order to take into account variations in the macroeconomic conditions. The correlation matrix for all the control variables included in the model is displayed in Appendix 1, suggesting low correlation levels among the regressors. All controls are lagged by one year to reduce endogeneity issues. We also include in equation (1) firm fixed effects (φ_{i}) to control for time-invariant characteristics at the firm level, and take into account yearly exogenous shocks common to all countries included in our sample by adding year dummies into our model (σ_t). Finally, ϵ_{it} is the error term. Serial correlation is a well-known issue in the estimation of DiD models using panel data since the work by Bertrand et al. (2004). A solution typically proposed in the econometric literature is to cluster using a cross-sectional dimension of the data, for which there are a sufficient number of clusters (Cameron and Trivedi, 2005; Angrist and Pischke, 2009; Wing et al., 2018). We cluster the standard errors in our regressions at the firm level, assuming error independence across individual firms.

Finally, we turn our attention to a crucial identifying assumption imbedded the DiD framework, which is the parallel trends assumption. This implies that the outcome trends (i.e. TFP) would be the same in both treated and control units in the absence of treatment (i.e. the acquisition). The treatment then induces a deviation from this common (parallel) trend (Angrist and Pischke, 2009). The parallel trends assumption, although largely untestable, can be assessed to a certain extent using an approach proposed by Angrist and Pischke (2009). They propose augmenting the DiD equation, i.e. our equation (1), adding a time trend (t) and an interaction of the trend and the treatment dummy (T_{it}). If the coefficient of this

that the acquisition date is random). The use of PSM in the previous step lowers potential selection biases that could make the treatment non-random, supporting the aforementioned assumption.

interaction is statistically insignificant, it can be expected that the parallel trends assumption holds. Our estimated coefficient is 0.005, with standard error of 0.003, therefore statistically insignificant.[6]

4. Dataset

We use Orbis financial, sectoral classification (NACE Rev. 2) and legal data compiled and provided by Bureau van Dijk (BvD), for EU27 countries, plus the UK, for the period 2005 to 2018.[7] We perform a basic cleaning process, inspired by Gal (2013) and Bajgar et al. (2020), such as removing negative and zero values of the financial variables, or removing duplicate observations by ID, year and accounts consolidation type. We also exclude from the analysis firms with less than €1m total assets and five employees.[8] All financial data is expressed in Euros.

We obtain the information regarding acquisitions that took place in the countries and years analysed from Zephyr database, also provided by BvD. As such, the Zephyr extraction includes data for completed deals where the target firm is located in a EU27 country (plus United Kingdom) in the period 2008-2018. We include all cross-border acquisitions therefore including both EU and non-EU investors. In section 5.4 we will focus on investors located exclusively outside the EU27 and UK, which we refer to as foreign investors. We select completed and confirmed deals. Several selection steps were applied to this original sample of deals.[9] After the data cleaning process, Zephyr acquisitions data is merged with the aforementioned Orbis financial information.[10] Through this merging, the treated and control firm groups in each country are identified. Some cleaning criteria are also applied to the control firms group, in order to improve comparability. Acquired firms that were discarded throughout the Zephyr cleaning process (i.e. firms that were the target of domestic acquisitions, minority acquisitions, etc.) are removed, if present among the control firms.

[6] Further details and the full set of estimates are available from the authors upon request.
[7] We excluded data corresponding to the years 2019 and 2020 due to it being incomplete, and data corresponding to the years prior to 2008 because the number of available observations was significantly lower than in the time period selected.
[8] We selected unconsolidated accounts, except for firms that only reported consolidated accounts. We assess the robustness of the results to this selection choice in section 6.
[9] We select cross-border majority acquisitions only, and exclude mergers, avoiding the problem of the treated firm collapsing into the balance sheet of the parent company, which would create identification of the effects of mergers difficult and lead to potential confounding effects.
[10] We use the BvD ID variable in Zephyr and the corresponding BvD ID variable in the Orbis financial dataset.

Once the Zephyr acquisitions and Orbis financial data are merged, the resulting combined dataset is further completed with historical Orbis ownership information. The historic ownership data allows us to reconstruct ownership changes (or lack of them) for both control and target firms in our sample. The use of historical ownership information is important because it allows overcoming a common drawback faced by previous related analysis that also used Orbis (such as Carril-Caccia, 2020), which rely on the ownership status recorded in the last year of the sample. Control firms are also removed from the sample if there is a change in the GUO (Global Ultimate Owner) or the DUO (Domestic Ultimate Owner)[11] in the period analysed, and also if the GUO country of origin is located in EU27 (plus UK).

4.1 Variable description

Partial productivity measures, which relate a measure firm output to a single input used in production (typically labour), have been used to proxy firm level performance. Although these measures have the advantage that they are easy to compute and require relatively less data than TFP measures, they do not account for the use of intermediate inputs (Gal, 2013) or, more generally, they do not account for factor or output substitution (Latruffe, 2010). For these reasons, TFP is a preferred measure of firm level productivity, as it takes into account all factors of production (provided that there is enough data available for its computation). A widely used measure of TFP is obtained through the estimation of a production function, as the resulting estimated Solow's residuals:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + a_{it} + \gamma_{it} \tag{2}$$

Equation (2) displays a Cobb-Douglas production function, where y_{it} is firm total output, l_{it} is the labour (variable) input, k_{it} is the capital (fixed) input, a_{it} is the productivity shock, and γ_{it} is an error term that captures other shocks that are not know by the researcher or the producer. However, a well-known problem that affects the estimation of production functions such as the one in equation (2) is that of the presence of simultaneity and selection issues. This would bias the estimates obtained using standard econometric estimation techniques such as OLS. This is due to the simultaneity of the unobserved productivity shock a_{it} (which is unknown to the econometrician, but known to the firm) and input choices made by the firm (Van Biesebroeck, 2007). Control function approaches have been widely implemented in the empirical literature in order to remove this bias. In this paper, we use the Levinsohn and Petrin

[11] The Global Ultimate Owner refers to the company owner at the global level (i.e. beyond national borders) with at least 50.01% of company's shares. The Domestic Ultimate Owner refers to the company owner within the same country.

(2003) estimation approach.[12] This and alternative TFP estimation approaches, which we will use to assess the robustness of our results in section 6, are described in more detail in Appendix 3. The output and input variables included in the production function in equation (2) are obtained from the Orbis balance sheet data. We use value added as a measure of firm output.[13] We include two inputs, labour and capital. Labour is measured as the number of employees. In order to measure capital, we build a variable capturing firms' capital stock, based on firms' annual value of fixed assets and depreciation. This approach uses the Perpetual Inventory Method (PIM), as outlined in in Gal (2013) and Andrews et al. (2016). Finally, intermediate inputs are not available but are computed as the difference between operating revenue and (imputed) value added.[14]

The treatment dummy (T_{it} in equation (1)) used is coded using the information extracted from the Zephyr database. It is based on the date of completion for the acquisition provided in Zephyr (it equals one for treated firms, from the acquisition year onwards, and zero for treated firms pre-acquisitions, and for control firms). The firm level characteristics included as controls in the staggered DiD panel regression in equation (1) are also based on Orbis data. More specifically, we use Orbis information regarding the value of firms' total assets, the value of short term debt, the firms' operating profit and firms' cost (calculated by subtracting EBIT to operating revenues) to construct the controls in vector $\boldsymbol{X_{it-1}}$ in equation (1). The macro-economic indicators also included as controls in equation (1) are taken from the World Development Indicators dataset published by the World Bank.

Our final sample includes control and target firms located in 14 EU countries.[15] Table 1 displays descriptive statistics for the main variables included in the empirical model, for the control group and the target group. Target firms have substantially higher average value of total assets (i.e. are larger) than those in the control group. The average proportion of fixed assets on total assets is also larger for target firms. Control firms have on average lower value of loans over total assets and have higher operational costs

[12] The production function in equation (2) is estimated for each country and each NACE Rev. 2 broad sector category (i.e. one-digit) separately.
[13] Value added is available in Orbis. However, it has a large number of missing values in some countries. Following Gal (2013) and Bajgar et al. (2020), we impute missing observations of the value added variable internally using the sum of the cost of employees and EBITDA.
[14] All monetary values are deflated using sector and country specific price indices taken from the Klems database.
[15] Austria, Belgium, Germany, Denmark, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the UK. Although originally included in the Zephyr data extraction, the rest of EU27 countries did not have enough observations to compute TFP that could be used in subsequent analysis.

relative to turnover, compared to the target group. Target firms have higher average profits relative to total assets. The average level of TFP is higher for target firms, compared to the firms in the control group.

Table 1. Descriptive statistics

	Mean	Std. Dev.	Minimum	Maximum	Median
Control sample (Obs. = 1,362,621)					
ln(TFP)	11.28	0.75	-3.82	20.35	11.24
Total assets	17.93	52.07	1.00	415.27	4.00
Fixed Assets/Total Assets	0.27	0.64	0.00	137.31	0.18
Loans/Total Assets	0.10	0.96	0.00	845.59	0.03
Profits/Total Assets	0.05	1.45	-12.09	1,681.54	0.04
Op. costs/Turnover	1.73	834.51	0.00	973,323.00	0.97
Target sample (Obs. = 12,674)					
ln(TFP)	11.92	0.94	6.13	17.87	11.80
Total assets	83.32	124.64	1.00	415.27	27.13
Fixed Assets/Total Assets	0.64	7.84	0.00	296.00	0.11
Loans/Total Assets	0.23	3.49	0.00	350.94	0.03
Profits/Total Assets	0.16	1.41	-18.66	69.76	0.05
Op. costs/Turnover	0.98	2.67	0.02	299.25	0.95

Notes: The value of total assets is expressed in € millions. "Control" category includes non-acquired firms; "Target" category includes acquired firms (both pre- and post-acquisition). All variables are computed based on Orbis data.

5. Results

5.1 Probability of acquisition

The coefficients obtained in the estimation of the logit model used to calculate the PS are provided in Appendix 2. The positive coefficient of the log of TFP variable indicates that, within a given industry and country, acquirers prefer target firms that operated with higher productivity levels pre-acquisition. This finding is in line with previous research such as Harris and Robinson (2002) or Salis (2008). The literature refers to this phenomenon as "cherry picking" (Girma et al., 2007). Acquirers also appeared to prefer larger target firms, although the negative sign of the squared terms of the log of the number of employees indicate that the probability of being acquired is reduced as firms become larger above a certain threshold. On the other hand, being older and obtaining less profit per unit of asset have negative impacts on the probability of target firms being acquired.

5.2 Baseline analysis

Table 2 displays the coefficients obtained after estimating a weighted (using the computed IPTW) equation (1) pooling all the data, for all countries and sectors, in our sample. The estimates in specification

(3) of Table 2 correspond to our baseline model, which includes the full set of controls $\boldsymbol{X_{it-1}}$ and $\boldsymbol{Z_{ct-1}}$, as well as year and firm FE, in equation (1). As a robustness check, in specification (1) we estimate the model without including firm-level controls (except for total assets) or macro-economic controls, and in specification (2) we estimate the model omitting the macro-economic controls only. Comparing the estimates in specifications (1) and (2) with those in specification (3) indicates that the control variables are not driving the estimated effect of the acquisition captured by our post-treatment dummy (i.e. T_{it} in equation (1)).

Table 2. Baseline analysis

	(1)	(2)	(3)	(4) t_0	(5) t+1	(6) t+2	(7) t+3
Treat*Post	-0.067***	-0.073***	-0.073***	-0.066**	-0.067***	-0.067***	-0.068***
	(0.026)	(0.025)	(0.026)	(0.028)	(0.025)	(0.025)	(0.025)
ln(Total Assets)$_{t-1}$	0.059	0.033	0.033	0.151***	0.043	0.059	0.034
	(0.080)	(0.077)	(0.077)	(0.042)	(0.100)	(0.086)	(0.088)
ln(Fixed Assets/Total Assets)$_{t-1}$		-0.578	-0.579	-0.258*	-0.096	-0.166	-0.583
		(0.408)	(0.405)	(0.156)	(0.321)	(0.282)	(0.441)
ln(Loans/Total Assets)$_{t-1}$		-0.020	-0.016	0.385*	0.228	0.065	0.049
		(0.204)	(0.207)	(0.208)	(0.246)	(0.227)	(0.213)
ln(Op. costs/Turnover)$_{t-1}$		-1.695***	-1.692***	-1.403***	-1.581***	-1.566***	-1.628***
		(0.356)	(0.354)	(0.457)	(0.432)	(0.400)	(0.373)
ln(Profits/Total Assets)$_{t-1}$		0.033	0.034	-0.114	-0.038	0.016	-0.048
		(0.153)	(0.152)	(0.214)	(0.183)	(0.147)	(0.179)
Observations	1,375,320	1,375,295	1,375,295	1,370,835	1,372,360	1,373,450	1,374,218
R-squared	0.775	0.783	0.783	0.823	0.802	0.797	0.785
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	No	No	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. Specifications (4) to (7) show the cumulated effect of acquisitions adding one year per time, up to t+3. *** p<0.01, ** p<0.05, * p<0.1.

As already explained in section 3.1, our main coefficient of interest is α_1 in equation (1), which captures the effect of the acquisition on the TFP of the acquired firms. This coefficient is displayed in the first row of Table 2. Focusing on our baseline model in specification (3), the cumulative effect of the acquisition on TFP appears to be negative and statistically significant at the 1% level. A weak negative link between a cross-border acquisition and the productivity of the target firm was previously identified (for example, in Girma and Görg, 2002, or in Harris and Robinson, 2002, for foreign acquired firms in the UK in both analyses). The negative impact could potentially be arising from several factors, or more likely, a combination of them. The lack of productivity improvements observed post-acquisition might be linked to the acquired firms being more productive (as suggested by the logit regression estimates discussed in section 5.1) than the acquiring firms (Salis, 2008). In this context, it could be the case that the assets of the acquired firms are being transferred to the acquiring firm leading to downgrading of European firms' production capabilities. As already noted in section 2, it is likely that this behaviour could be linked to specificities relating to the sector or the country of origin of the acquiring firm. These aspects are explored in the next section. Finally, other authors, have pointed to difficulties in incorporating the acquired firm in the operations and structure of the acquiring firm (Harris and Robinson, 2002), leading to managerial dis-synergies that negatively affect productivity. In terms of the firm level characteristics included as controls in the baseline model, we find that the effect of operational costs per unit of output on productivity is negative. This result could be linked to firms failing to exploit economies of scale, with the consequent productivity deterioration.

The baseline result refers to the overall effect on average, of the acquisition. In order to obtain more detail regarding the cumulative evolution of the effect of being acquired in the years after the acquisition, we re-estimate the baseline model using an alternative specification of the post-treatment dummy to detect the effects on impact, and adding up one year per time up to t+3.[16] Specifications (4) to (7) in Table 2 display the regression coefficients obtained through this exercise. The post-treatment coefficients are again negative and statistically significant at the 1% level, except the coefficient on the year of the acquisition (t_0), which is significant at the 5% level. The magnitude of these coefficients is smaller than that of the coefficient in the baseline model, particularly in the year of the acquisition, although in increases slowly in the years after. Different time effects post-acquisition have been identified in the literature before, for example in Schiffbauer et al. (2017) or Salis (2008). The differing impact through time of the acquisition is likely to be linked to reorganization costs in the short to medium run (Schiffbauer et al., 2017), or to progressive assimilation problems arising after the acquisition took place (Salis, 2008).

A potential concern affecting our baseline estimate is that there may be confounding unobservable and time-varying effects on the TFP of the treated and control groups, independent of the acquisition. We assess this issue employing a series of falsification, or placebo, tests to uncover potential systematic biases. We construct a series of artificial treatment dummies for the acquisition timing. We assign the acquisition year to be ahead of the actual event by one year, two years, and three years, as well as one, two, and three years before. This experiment tests for any changes in productivity before and after the acquisition on a year-by-year basis. The estimates of the re-specified treatment dummies are shown in

[16] We re-specify this dummy equal to 1 only in the first year in which firms are acquired (t_0), then equal to 1 on the year they are acquired and the year after that (t+1) and so on, up to t+3.

Table 3, with specifications (1) to (3) showing the leads, and specifications (4) to (6) showing the lagged effects. All the coefficients are statistically insignificant, indicating that there are no substantial differences among the treated and control groups if we assign the acquisition year fictionally to the periods before or after. In addition, the lack of statistical significance of the coefficients of the pre-acquisition dummies suggest that our results are not driven by pre-treatment trends in productivity (Beck et al., 2000; Dasgupta et al., 2017).

Table 3. Falsification tests

	(1) 1-year ahead	(2) 2-years ahead	(3) 3-years ahead	(4) 1-year before	(5) 2-years before	(6) 3-years before
Treat*Post	-0.042	0.001	0.028	0.000	0.015	0.046
	(0.033)	(0.046)	(0.059)	(0.029)	(0.037)	(0.045)
Observations	1,375,295	1,375,295	1,375,295	1,375,295	1,375,295	1,375,295
R-squared	0.783	0.783	0.783	0.783	0.783	0.783
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Sectoral analysis

The cumulative overall effect identified in the previous section however could potentially be masking variation of the effects of acquisitions across different sectors of the economy. In order to explore sector heterogeneity in more detail, we estimate our baseline model according to the NACE Rev. 2 one-digit in which target firms operate. The results of the sector specific estimations are displayed in Table 4.

Interestingly, this more detailed analysis highlights that the effects of acquisitions are concentrated in three out of the nine sectors included. Cross-border acquisitions in the primary sector category have a negative and statistically significant effect on firm level productivity, although only at the 10% level, while for the case of acquisitions in manufacturing and utilities sectors, the effect is also negative, but statistically significant at the 1% level. Despite the lack of statistically significance of the treatment coefficients in the remaining sectors, the coefficients are also negative in the majority of cases, except for the construction and financial and insurance sectors.

Table 4. Sectoral analysis

	(1) Primary	(2) Manufacturing	(3) Utilities	(4) Construction	(5) Services	(6) ICT	(7) Finance & Ins.	(8) Real estate	(9) Prof. & Scientific
Treat*Post	-0.365*	-0.120***	-0.254***	0.066	-0.065	-0.041	0.198	-0.108	-0.048
	(0.199)	(0.031)	(0.080)	(0.081)	(0.044)	(0.061)	(0.121)	(0.213)	(0.108)
ln(Total Assets)$_{t-1}$	-1.122***	0.097	0.020	-0.182	0.162***	0.150**	0.825*	0.455	-0.047
	(0.349)	(0.061)	(0.136)	(0.116)	(0.061)	(0.068)	(0.429)	(0.298)	(0.101)
ln(Fixed Assets/Total Assets)$_{t-1}$	3.065**	-0.410**	-0.657	-0.684	-1.569**	0.688	0.295	-0.310	-1.499**
	(1.356)	(0.168)	(0.930)	(0.440)	(0.734)	(0.782)	(1.276)	(0.678)	(0.630)
ln(Loans/Total Assets)$_{t-1}$	1.870	-0.262	-0.882**	1.010	-0.340	-0.229	-0.136	1.082	0.348
	(1.712)	(0.309)	(0.403)	(0.693)	(0.310)	(0.381)	(0.844)	(1.149)	(0.400)
ln(Op. costs/Turnover)$_{t-1}$	-0.494	-1.973***	0.382	-3.146***	-1.884***	-1.190*	-0.185	0.745	-1.795*
	(1.575)	(0.389)	(0.961)	(1.131)	(0.364)	(0.670)	(0.845)	(0.873)	(1.039)
ln(Profits/Total Assets)$_{t-1}$	2.525	0.218	0.317	-0.078	-0.275	-0.346*	0.189	0.720	-0.218
	(1.816)	(0.234)	(0.593)	(0.518)	(0.232)	(0.182)	(0.251)	(0.565)	(0.339)
Observations	37,748	478,763	32,443	140,601	519,450	45,260	18,615	36,126	66,289
R-squared	0.804	0.754	0.888	0.830	0.728	0.748	0.733	0.758	0.639
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. NACE Rev. 2 letters: Primary (A, B), Manufacturing (C), Utilities (D, E), Construction (F), Services (G, H, I), ICT (J), Finance and Insurance. (K), Real estate (L), Professional and Scientific (M).

In light of the results obtained in Table 4, we explore in more detail cross-border acquisitions in the manufacturing sector, as this broadly defined sector category is characterised by the large heterogeneity of firms it includes,[17] in terms of aspects such as specialisation or technology innovation. It also groups the largest share of acquisitions in our sample, accounting for 49 per cent of all deals. Previous literature has identified the knowledge intensive versus less knowledge intensive distinction as a factor likely to be relevant in terms of potential negative or positive effects of an acquisition on firm level productivity (Salis, 2008; Pittiglio and Reganati, 2018). This distinction is also highly relevant for services activities, which groups the second largest share of acquisitions in our data (19 per cent). For these reasons, the remaining sectoral analysis presented in this section will focus on sectoral variation defined in terms of technology innovation and knowledge intensity for manufacturing and services firms.

We exploit a Eurostat classification based on technological intensity and on Research and Development, for manufacturing production, and on the share of tertiary educated labour, for services activities (in both cases defined at the NACE Rev. 2 two-digit classification).[18] More specifically, we build two sectoral classifications according to the degree of technological development or knowledge intensity of the activities carried out by manufacturing and services firms, respectively, in our sample: i) we group firms in the manufacturing sector according to the technological level, or intensity (based on Research and Development expenditure over value added) in two categories, being high/medium-high technology and medium-low/low technology manufacturing; ii) we group firms in the services sectors according to knowledge intensity (based on tertiary educated persons employed) in two categories, being knowledge intensive services and less knowledge intensive services.[19] Again, we estimate our baseline staggered DiD panel regression for each of these four alternative sectoral groupings of manufacturing and services firms, and provide the estimates in Table 5.

The effect of cross-border acquisitions on the TFP of target firms is negative and statistically significant when acquisitions take place both in high and medium-high, and in medium-low and low technology manufacturing, as presented in specifications (1) and (2) in Table 5. Previous empirical research on cross-

[17] In order to explore whether the lack of statistical significance of the effects of cross-border acquisitions was linked to the broad definition of the sector categories used in Table 3, we also estimate the staggered DiD regressions at the NACE Rev. 2 2-digit level (instead of NACE Letter). Results were confirmed, in fact, these estimates failed to identify effects of acquisitions in more detail, as the coefficients of interest were mostly statistically insignificant. Where significant, the treatment coefficients confirm the negative significant effects identified in the broader letter category for manufacturing (tables available upon request from the authors).

[18] https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm#annex1580829488131.

[19] For details on the definition of high and low technology manufacturing and knowledge/less knowledge intensive services see https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

border acquisitions and productivity has pointed out at the possibility that in sectors characterised by technologically advanced activities, the degree of technological transfer from the target to the acquiring firms is more likely to be larger, with consequent productivity deterioration in the target firm (Salis, 2008; Pittiglio and Reganati, 2018). The productivity reductions identified for target firms in the medium-low and low technology manufacturing post-acquisition could be due several factors pointed out in previous literature. One factor could be dis-synergies arising post-acquisition, particularly if acquiring and target firms do not have complementary stocks of capital (Buckley et al., 2014). It can also be the case that acquisitions in lower technology manufacturing sectors diminish the productivity of the target firms if technologies are not transferable due to intangibles being less prevalent (Keller, 2004). Finally, the productivity reductions observed in low tech activities post-acquisitions could be due these sectors being mainly targeted by acquiring firms originating in emerging economies, thus characterised by lower productivity (Sanfilippo, 2015), that may negatively influence productivity of the target firms.

Table 5. Knowledge vs less-knowledge insensitive activities

	Manufacturing		Services	
	(1)	(2)	(3)	(4)
	High/Medium-high techn.	Medium-low/Low techn.	K. I. Services	Less K. I. Services
Treat*Post	-0.090**	-0.140***	0.007	-0.048
	(0.045)	(0.041)	(0.064)	(0.049)
ln(Total Assets)$_{t-1}$	-0.041	0.170**	0.141	-0.010
	(0.067)	(0.078)	(0.111)	(0.165)
ln(Fixed Assets/Total Assets)$_{t-1}$	-0.311	-0.408*	-0.715	-0.776
	(0.243)	(0.212)	(0.529)	(0.964)
ln(Loans/Total Assets)$_{t-1}$	-0.013	-0.383	0.176	-0.201
	(0.199)	(0.420)	(0.302)	(0.351)
ln(Op. costs/Turnover)$_{t-1}$	-1.357**	-2.450***	-1.213*	-2.224***
	(0.566)	(0.546)	(0.644)	(0.669)
ln(Profits/Total Assets)$_{t-1}$	0.136	0.223	-0.061	-0.212
	(0.227)	(0.307)	(0.206)	(0.258)
Observations	126,368	352,395	134,018	560,373
R-squared	0.726	0.768	0.713	0.695
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The effect of cross-border acquisitions on acquired firms TFP is statistically insignificant for the case of acquisitions that took place in services related activities, regardless of the knowledge intensity level (as shown in specifications (4) and (5) in Table 5). Due to the lack of statistical significance of the estimates obtained for the services sectors in Tables 4 and 5, we focus the remaining analysis in section 5.4 on the manufacturing sector.

5.4 Foreign acquirer ultimate owner

In section 2 we highlighted how in recent literature particular attention has been paid to the importance of accounting for the country of origin of the acquiring firm in terms of identifying potential pervasive effects of cross-border acquisitions on productivity of the target firm. In this analysis, we go a step further and exploit the detailed historical ownership information we have for firms in our sample and use it to classify acquiring firms according to the country of origin of their Global Ultimate Owner (GUO50[20]).

In order to explore whether the negative effects we have identified in previous sections present variation once we account for the investor's GUO origin, we classify acquiring firms according to the country of origin of their GUO in four geographical regions: US, emerging economies,[21] Offshore Financial Centres (OFCs),[22] and Rest of the World (RoW). Acquisitions where the GUO originates in the US represent 22.2 per cent of the total number of acquisitions in our data, while the percentages for emerging economies, OFCs and RoW are 6.3, 2.4 and 13.1 percent, respectively. In order to also account for sectoral variation, we estimate separated regressions, within each of the four GUO origin categories, for high and low technology manufacturing activities (i.e. corresponding to specifications (1) and (2) in Table 5) separately. Results for these estimations are provided in Table 6.

[20] Defined in Orbis as the global ultimate owner located anywhere in the world, but with a minimum of 50.01% share ownership.
[21] Defined according to S&P DJI emerging market 2020 classification (the classification can be consulted in: https://www.spglobal.com/spdji/en/documents/indexnews/announcements/20200819-1206359/1206359_spdji2020countryclassificationconsultation8-19-2020.pdf; and the methodology can be consulted in: https://www.spglobal.com/spdji/en/documents/index-policies/methodology-country-classification.pdf). The countries included are United Arab Emirates, Brazil, Chile, China, Egypt, Indonesia, India, Kuwait, Mexico, Malaysia, Peru, the Philippines, Pakistan, Qatar, the Russian Federation, Saudi Arabia, Thailand, Turkey, Taiwan, and South Africa.
[22] The countries included in this category are Andorra, Barbados, Bermuda, the Bahamas, Gibraltar, the Cayman Islands, Liechtenstein, Monaco, Marshall Islands, Panama, and the Virgin Islands (British).

Table 6. High vs low tech. manufacturing activities, by acquirers' country of origin

	US		Emerging economies		Offshore Fin. Centres		RoW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High tech. Mnf.	Low tech. Mnf.	High tech. Mnf.	Low tech. Mnf.	High tech. Mnf.	Low tech. Mnf.	High tech. Mnf.	Low tech. Mnf.
Treat*Post	-0.027	-0.011	-0.254**	-0.090	-0.345***	-0.105	-0.161	-0.279*
	(0.065)	(0.041)	(0.111)	(0.056)	(0.124)	(0.116)	(0.155)	(0.143)
ln(Total Assets)$_{t-1}$	0.093	0.187***	-0.043	0.103**	-0.062	0.112***	-0.171	0.451***
	(0.094)	(0.049)	(0.071)	(0.052)	(0.151)	(0.017)	(0.158)	(0.169)
ln(Fixed Assets/Total Assets)$_{t-1}$	-0.230	-0.467***	-1.328**	-0.540***	0.410	-0.210***	-0.764***	0.528
	(0.381)	(0.107)	(0.651)	(0.171)	(0.560)	(0.052)	(0.265)	(0.464)
ln(Loans/Total Assets)$_{t-1}$	-0.266	0.177	-0.080	0.124	0.339	-0.011	0.076	-1.417*
	(0.245)	(0.155)	(0.175)	(0.130)	(0.322)	(0.051)	(0.226)	(0.742)
ln(Op. costs/Turnover)$_{t-1}$	-0.943	-0.320	-1.571***	-1.213***	-2.362**	-0.367	-1.796**	-1.126**
	(1.145)	(0.460)	(0.574)	(0.315)	(1.174)	(0.278)	(0.701)	(0.546)
ln(Profits/Total Assets)$_{t-1}$	0.446	1.702***	-0.607	0.846*	-0.456	0.609***	-0.236	1.082***
	(0.420)	(0.218)	(0.408)	(0.449)	(0.701)	(0.097)	(0.319)	(0.370)
Observations	124,070	349,821	123,477	349,596	123,320	349,413	123,641	349,674
R-squared	0.782	0.868	0.812	0.822	0.722	0.826	0.730	0.745
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Emerging economies classification is described in footnote 21, and OFCs in footnote 22. RoW indicates Rest of the World. The acquirer's country of origin is defined using, when available, the location of the Global Ultimate Owner, otherwise the location of the acquirer.

The coefficient of the treatment dummy in specifications (1) and (2) in Table 6, corresponding to acquisitions made by foreign investors with GUOs originating in the US, is statistically insignificant, regardless of the sectoral classification. However, when foreign acquiring firms with GUOs originating in emerging economies (specification (3) in Table 6) or in OFCs (specification (5)) are involved, the productivity of target firms is affected negatively, with the negative effect being statistically significant only for acquisitions that take place in high technology manufacturing. These estimates might indicate that foreign acquiring firms involved in these acquisitions not able to improve productivity of the target firms post-acquisition, which might be possibly linked to productivity differentials between target and foreign investor (Sanfilippo, 2015). By contrast, foreign acquisitions involving acquiring firms with GUOs that originate in the RoW (specification (8)) have a negative effect on the productivity of the target firm, in this case restricted to acquisitions in low technology sectors.

6. Robustness checks

In this section, we implement a series of robustness checks to our baseline model. The first robustness check is displayed in specification (1) in Table 7. The estimates displayed are obtained including only acquirers whose GUO originates in an EU country. Cross-border acquisitions where the GUO of the acquiring firm is located in an EU country represent about 56 per cent of all acquisitions in our data. While the negative coefficient is still present, it is only statistically significant at the 10% level. Although with lower statistical significance, the negative effect of cross-border acquisitions of EU targets by investors with EU GUOs might be linked to these acquisitions to increase market concentration (Bjorvatn, 2004). This might reduce productivity improvement at the industry level (Bertrand and Zitouna, 2008), due to, for example, increased market shares by cross-border investors translating into a share reduction for local firms, which would in turn hinder their exploitation of scale economies (Djankov and Hoekman, 2000).

Three further alternative sample specifications are used in order to test the robustness of the baseline model presented in Table 2. First, the earlier part of the time period included in our analysis corresponds to the years after the start of the 2008 financial crisis. As displayed in Figure 1, the TFP estimates corresponding to the earlier period in our sample are characterised by higher TFP growth volatility, when compared to the latter years of the period included. In order to test whether these TFP changes are driving the treatment effects uncovered, we re-estimate our model excluding the years prior to 2011 from the sample. The alternative set of estimates is presented in specification (2) in Table 7. The estimates obtained using the full time period for the analysis are robust. Second, our baseline model was estimated including both SMEs and large firms. However, financial data corresponding to micro firms[23] in Orbis is often deemed as less reliable, and more importantly, these firms are not well represented in the Orbis database (Bajgar et al., 2020). In order to assess whether the presence of these firms in the sample is generating confounding effects to our estimated treatment effect, we re-estimate the baseline model excluding micro firms from the sample (this discards approximately 14 per cent of the original estimation sample). The alternative set of coefficients are displayed in Table 7 specification (3). Again, the baseline estimates appear robust to the exclusion or inclusion of micro firms. Third, we assess the robustness of our estimates to the possibility that for firms with subsidiaries, a cross-border acquisition would affect the productivity of the overall group, and not only of the acquired company. In this case, positive or negative effects related to the acquisition could be transferred to the subsidiaries generating a confounding factor biasing

[23] Defined according to the European Commission classification as those with less than 10 employees and an annual turnover, or an annual balance sheet total, equal or lower than 2 million Euro (European Commission, 2003).

our estimates. For this purpose, we exploit the account consolidation information in Orbis, and select balance sheet data that corresponds only to firms with no consolidated companions, meaning that they are stand-alone companies having no subsidiaries.[24] The resulting set of coefficients are displayed in Table 7 specification (4). Again, our main results are confirmed.

Table 7. Robustness on baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Matched samples		
	EU acquirers	No debt crisis	No micro	No Subsidiaries	PSM	MDM	CEM
Treat*Post	-0.057*	-0.082***	-0.076***	-0.118***	-0.060***	-0.114***	-0.040***
	(0.031)	(0.028)	(0.027)	(0.024)	(0.014)	(0.017)	(0.012)
ln(Total Assets)$_{t-1}$	0.010	0.018	0.033	0.105***	0.092***	0.129***	0.085***
	(0.112)	(0.063)	(0.079)	(0.039)	(0.021)	(0.027)	(0.016)
ln(Fixed Assets/Total Assets)$_{t-1}$	-0.610	-0.776*	-0.642	-0.439***	-0.371***	-0.622***	-0.284***
	(0.536)	(0.423)	(0.416)	(0.163)	(0.128)	(0.139)	(0.100)
ln(Loans/Total Assets)$_{t-1}$	-0.225	-0.059	-0.123	-0.074	0.061	-0.170	-0.039
	(0.211)	(0.226)	(0.211)	(0.238)	(0.086)	(0.113)	(0.071)
ln(Op. costs/Turnover)$_{t-1}$	-2.001***	-1.224***	-1.692***	-1.855***	-1.004***	-1.549***	-0.925***
	(0.542)	(0.367)	(0.375)	(0.444)	(0.202)	(0.357)	(0.185)
ln(Profits/Total Assets)$_{t-1}$	-0.039	0.113	0.026	-0.018	0.063	0.210	0.157**
	(0.186)	(0.194)	(0.154)	(0.185)	(0.073)	(0.168)	(0.064)
Observations	1,369,520	1,232,612	1,216,080	1,290,722	17,055	1,336,156	35,139
R-squared	0.806	0.795	0.771	0.822	0.842	0.822	0.849
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A further set of sensitivity analyses relate to the approach followed to obtain a comparable control group in our baseline model. As discussed, in Tables 2 to 6 we re-weight our sample using inverse probability weights computed based on the PS. Alternatively, we now test the sensitivity of our results to the use of matched samples, instead of inverse probability weights.[25] More specifically, we re-estimate our baseline model on matched samples obtained applying PSM, as well as other possible matching methods suggested as more adequate in King and Nielsen (2019), which are MDM and EM. These alternative set of estimates are displayed in specifications (5) to (7) in Table 7. In specification (5) we use a matched sample obtained applying nearest-neighbour PSM (with 10 neighbours). This PSM is based on

[24] Account consolidation type U1, as defined by Orbis. This excludes 6.2 per cent of our estimation sample.

[25] The baseline model used in Tables 2 to 6 was ultimately chosen based on the unsatisfactory balancing test obtained when matching using MDM or EM, which did not suggest satisfactory matching performance (results available upon request). The results of the balancing tests for the PSM are provided in Appendix 2.

the PS estimates used to compute the IPTW outlined in section 3 (i.e. estimated using a logit regression and three years of pre-treatment characteristics). In specification (6) we match our treated and control observations using MDM, and in specification (7) using Coarsened Exact Matching (CEM). All three matching approaches are based on equivalent sets of covariates, and match on three years of pre-treatment characteristics. The results in Table 7 suggest that our baseline results in Table 2 do not suffer from potential biases due to the approach followed to obtain comparable treated and control firms.

By applying IPTW re-weighting/matching combined with panel DID estimation, issues with selection on observables as well as time-invariant unobservable firm characteristics are taken into account. However, confounding effects arising from the presence of potential time-variant unobserved heterogeneity driving both the cross-border acquisition and firm TFP might still be present. In order to explore whether the presence of this type of heterogeneity is a confounding factor, we re-estimate our baseline specification using panel FE IV estimation. We use two-year lags of the control variables in the model as instruments for the treatment dummy variable. These estimates are shown in specification (5) in Table A4.1, Appendix 4. The negative and statistically significant coefficient for the treatment dummy is confirmed by this alternative estimation approach.

Finally, additional sensitivity tests relate to the estimation of the TFP scores. As briefly outlined in section 4 (and in Appendix 3), alternative TFP estimation techniques exist such as the Olley and Pakes (1996) approach, or the use of OLS or FE regressions to obtain the production function residuals. In addition, partial productivity measures, such as labour productivity, can be computed using our dataset. On top of the Levinsohn and Petrin (2003) TFP estimation approach, we also computed TFP using the aforementioned three alternative approaches, as well as the partial productivity of labour. We then estimate our baseline staggered DiD model using each of these four alternative productivity measures as dependent variables, with results presented in Table A4.1, in Appendix 4, specifications (1) to (4). Again, the baseline model in Table 2 is robust to the TFP estimation approach, as well as to the use of labour productivity.

7. Conclusions

For the past decade, European countries have experienced a generalised productivity slowdown. In addition, the political debate about foreign acquisitions of European firms, particularly in strategic sectors, has become rather prevalent in recent years, leading to the adoption of a European FDI Screening mechanism, in place since October 2020. Despite these political discussions, empirical literature on the effect of cross-border acquisitions on firm level productivity has failed to provide conclusive evidence regarding their impact on target firm performance. In this context, we attempt to provide further empirical evidence regarding the causal effect of cross-border acquisitions on firm-level productivity of foreign acquired EU firms between 2008 and 2018.

The traditional view is that productivity improvements in target firms arising from FDI are driven by superior production technology or intangible assets owned by the foreign acquiring firm (Djankov and Hoekman, 2000). This is not always the case however, as it is largely dependent on factors such as the sector they operate in (i.e. vertical vs horizontal acquisition, spillover effects) or firm level characteristics (i.e. pre-acquisition firm performance, technological capacity, wages, etc.). The evolving nature and mobility of firm assets and management in recent years has also introduced the notion that location is an increasingly important factor when determining the relation between FDI and firm competitiveness (Dunning, 2009). In fact, the prevalence of the effects emerging from the parent firm has been challenged in terms of acquisitions coming from emerging economies into developed countries (Buckley et al., 2014).

In our empirical analysis, our identification strategy relies on inverse probability weighting combined with panel staggered DiD (Athey and Imbens, 2018), which serves the double purpose of removing selection bias and endogeneity issues while identifying a causal effect of acquisitions that happen at different points in time during the years included in our sample. Thus, we are able to identify the effects of cross-border acquisition on the TFP of the target firms. We focus our sample of target firms on those located in 14 EU economies, acquired in the years from 2008 to 2018.

We uncover evidence suggesting a negative and statistically significant effect of cross-border acquisitions on TFP of European firms in recent years. In line with our findings, previous research such as Girma and Görg (2002), Harris and Robinson (2002) or Schiffbauer et al. (2017) found also negative, yet weaker evidence of the effect of foreign acquisitions on productivity. It is possible that the reason why we find a clearer effect is linked to the careful cleaning of our treatment and control groups in combination with our different estimation approach (i.e. IPTW combined with panel staggered DiD).

Moreover, we disentangle acquisitions effects at a more granular level, exploring variability in terms of sector of operation and country of origin of foreign (i.e. non-EU) investors. Our estimates show some heterogeneity in the effects of cross-border acquisitions. The negative and statistically significant effect is observed for acquisitions that took place in the manufacturing, and the primary and utilities sectors. For the case of manufacturing, this negative effect is found in both high-tech and low-tech activities. Some reasons for the negative relationship in manufacturing have been suggested in the literature. For the case of sectors characterised by technologically advanced activities, the productivity deterioration in the target firm post-acquisition could be linked to a large degree of technological transfer from the target to the acquiring firms being more likely (Salis, 2008; Pittiglio and Reganati, 2018). The productivity reductions identified for low-tech target firms could be due to dis-synergies if acquiring and target firms do not have complementary stocks of capital (Buckley et al., 2014). It can also be the case that acquisitions in lower technology manufacturing sectors diminish the productivity of the target firms if technologies are not transferable due to intangibles being less prevalent (Keller, 2004). Finally, our estimates suggest that the country of origin of the GUO of the acquiring firm also appears to matter. For the case of GUOs in emerging economies and OFCs, we find that the negative effect on productivity of target firms relate to high technology manufacturing sectors, possibly suggesting that in sectors characterized by more knowledge intensive activities acquiring firms from emerging countries involved are inducing lower productivity to the targets, maybe due to productivity differentials (Sanfilippo, 2015).

In sum, while it is generally believed that acquisitions increase productivity, we suggest that this effect cannot be taken for granted. We contribute to the policy debate suggesting that policies implemented with the sole goal of fostering cross-border investments cannot be considered as a sufficient tool to counteract the long lasting low productivity present in our economies. Consequently, policy makers may consider a more comprehensive approach, leveraging on a series of instruments able to tackle the secular stagnation issue from different angles, such as fostering competitiveness and innovation. In addition, reforms should consider that different sectors might react unevenly.

Some limitations are present in the empirical analysis provided in this paper. Measuring the extent to which spillovers are driving our results is challenging in the frame of our analysis, and further research could aim at disentangling potential spillover effects. On top of this, it would be interesting to deepen the dynamic of competition, controlling for market concentration, especially at the sectoral level. In addition, an emerging topic in the foreign acquisitions literature relates to the type of entity of the acquirer, or its GUO, and in particular whether they are state owned or state controlled enterprises (Carril-Caccia, 2020). Therefore, further analysis exploring competition issues and the status of the acquiring firm could provide useful empirical evidence to the policy debate.

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Appendix 1

Table A1. Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	ln(Total Assets)	1.000						
(2)	ln(Fixed Assets/Total Assets)	0.039	1.000					
(3)	ln(Loans/Total Assets)	0.036	-0.051	1.000				
(4)	ln(Op. costs/Turnover)	-0.179	-0.081	0.184	1.000			
(5)	ln(Profits/Total Assets)	0.001	-0.132	-0.187	-0.549	1.000		
(6)	Inflation	0.049	0.018	0.065	0.006	-0.015	1.000	
(7)	ln(PerCapitaGDP)	0.232	-0.026	-0.029	-0.013	0.136	0.215	1.000

Appendix 2 – PSM tests

In this appendix, we detail the PSM approach. Table A2 shows the logit regression output of the PSM. Table A3 displays the t-tests results for equality of means in the matched sample for the continuous variables included in PSM logit regression. The t-tests are obtained through a regression of each of the variables displayed on the treatment (i.e. acquisition) indicator, with the regression being weighted using the PSM weights estimated and the on-support sample. The test results are statistically insignificant in all cases, indicating that the matching was successful. Figure A1 also indicates that the standardised bias for the covariates displayed is significantly reduced in the matched sample, when compared to the unmatched one. Finally, we also provide some overall measures of covariate imbalance, this time for both the matched and unmatched samples, calculated including the full set of covariates used in the propensity score computation, as detailed in Table A4. First we display the pseudo-R^2 from logit estimation of the propensity score the full set of covariates included in the PSM exercise on unmatched and matched samples before and after matching. Second, we show the p-values of the likelihood-ratio test of the joint insignificance of all the covariates before and after matching. These two results indicate that the matched sample has lost all the predicting power as a result of the matching exercise. Third, we display the Rubin's B, with recommended values lower than 25, and Rubin's R scores, with recommended values between 0.5 and 2 (Rubin, 2001). The scores obtained indicate that the matched sample is sufficiently balanced.

Table A2.1. Propensity Score Matching, Logit regression output

	(1)		*(cont.)*
$\log(TFP)_{t-1}$	0.364***	$\ln(Op.\ costs/Total\ Assets)_{t-2}$	0.248
	(0.065)		(0.344)
$Ln(No.\ Employees)_{t-1}$	1.881***	$\ln(Profits/Total\ Assets)_{t-2}$	-0.263
	(0.297)		(0.206)
$Ln(No.\ Employees)^2_{t-1}$	-0.148***	$\ln(Age)_{t-2}$	0.667
	(0.030)		(2.587)
$\ln(Debts/Total\ Assets)_{t-1}$	0.250	$\ln(Age)^2_{t-2}$	-18.221***
	(0.192)		(5.267)
$\ln(Op.\ costs/Total\ Assets)_{t-1}$	0.049	$\log(TFP)_{t-3}$	-0.006
	(0.275)		(0.059)
$\ln(Profits/Total\ Assets)_{t-1}$	-0.238	$Ln(No.\ Employees)_{t-3}$	-0.382
	(0.180)		(0.280)
$\ln(Age)_{t-1}$	-5.030***	$Ln(No.\ Employees)^2_{t-3}$	0.037
	(2.559)		(0.029)
$\ln(Age)^2_{t-1}$	12.061***	$\ln(Debts/Total\ Assets)_{t-3}$	-0.294
	(3.279)		(0.189)
$\log(TFP)_{t-2}$	0.267***	$\ln(Op.\ costs/Total\ Assets)_{t-3}$	0.388
	(0.074)		(0.273)
$Ln(No.\ Employees)_{t-2}$	-0.327	$\ln(Profits/Total\ Assets)_{t-3}$	-0.548***
	(0.395)		(0.141)
$Ln(No.\ Employees)^2_{t-2}$	0.038	$\ln(Age)_{t-3}$	3.765***
	(0.041)		(0.946)
$\ln(Debts/Total\ Assets)_{t-2}$	-0.274	$\ln(Age)^2_{t-3}$	6.273***
	(0.242)		(2.048)
		Constant	-18.167***
			(0.832)
Observations	1,571,896		
Pseudo R-squared	0.160		
Log likelihood	4,903.17		
Country FE	Yes		
Sector FE	Yes		

Notes: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1.

Figure A2.1. Standardised % bias reductions

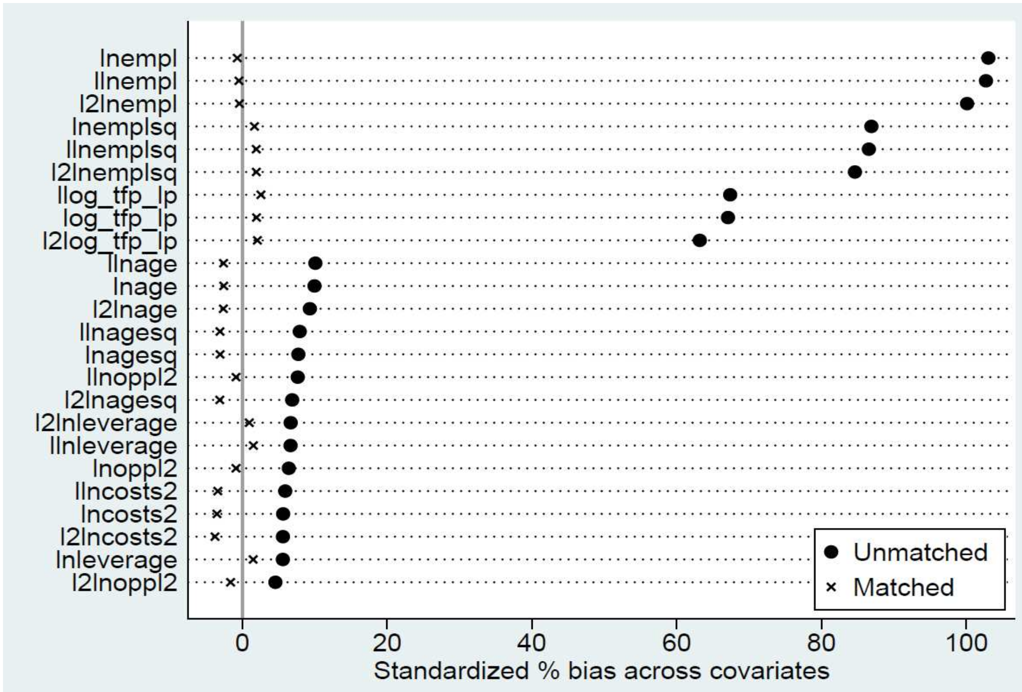

Table A2.2. Balancing tests

	Mean		Bias (%)	Bias reduction (%)	t-test p > t
	Treated	Control			
1 year pre-acquistion					
log(TFP)	11.909	11.892	2	97.1	0.551
Ln(No. Employees)	4.730	4.740	-0.7	99.3	0.842
Ln(No. Employees)^2	24.749	24.517	1.7	98.1	0.655
ln(Op. costs/Total Assets)	0.748	0.762	-3.5	38.3	0.253
ln(Profits/Total Assets)	0.184	0.182	1.5	73.1	0.653
ln(Debts/Total Assets)	0.054	0.055	-0.9	86.6	0.804
ln(Age)	2.715	2.749	-2.5	74.5	0.358
ln(Age)^2	8.711	8.874	-3.1	60.6	0.327
2 years pre-acquistion					
log(TFP)	11.891	11.869	2.6	96.2	0.453
Ln(No. Employees)	4.697	4.703	-0.5	99.6	0.898
Ln(No. Employees)^2	24.495	24.228	1.9	97.8	0.610
ln(Op. costs/Total Assets)	0.744	0.758	-3.4	43.2	0.268
ln(Profits/Total Assets)	0.190	0.187	1.5	76.9	0.644
ln(Debts/Total Assets)	0.053	0.054	-0.9	88.9	0.802
ln(Age)	2.653	2.687	-2.6	74.5	0.359
ln(Age)^2	8.418	8.583	-3.1	61.3	0.329
3 years pre-acquistion					
log(TFP)	11.843	11.825	2.1	96.7	0.549
Ln(No. Employees)	4.662	4.667	-0.4	99.6	0.913
Ln(No. Employees)^2	24.220	23.950	2	97.7	0.607
ln(Op. costs/Total Assets)	0.746	0.761	-3.8	33.2	0.225
ln(Profits/Total Assets)	0.194	0.192	1	85.4	0.771
ln(Debts/Total Assets)	0.045	0.047	-1.6	64.9	0.696
ln(Age)	2.582	2.616	-2.6	72.1	0.366
ln(Age)^2	8.115	8.280	-3.1	55.1	0.333

Notes: Matched sample tests.

Table A2.3. Additional balancing statistics

	(1)	(2)		(3)	
	Pseudo-R^2	LR chi^2	p>chi^2	B	R
Unmatched	0.16	5037.11	0.00	170.7*	1.10
Matched	0.01	27.46	1.00	16.60	1.25

Note: * if B>25%, R outside [0.5; 2]

Appendix 3 - Total factor productivity

Olley and Pakes (1996) proposed a semi-parametric estimation approach that controls for these biases, which allow obtaining consistent production function parameters and unbiased productivity estimates. In order to control for the correlation between a_{it} and the inputs, they relied on the assumption that future productivity is strictly increasing with respect to a_{it}, so firms that observe a positive productivity shock in period t will invest (Inv_{it}) more in that period, for any k_{it}. Variable inputs (l_{it}) are assumed to be unaffected by biases. This can be formalized as:

$$a_{it} = f^{-1}(Inv_{it}, k_{it}) = h(Inv_{it}, k_{it}) \quad (4)$$

By replacing the previous expression in the production function in equation (3) we obtain:

$$y_{it} = \beta_1 l_{it} + \varphi(Inv_{it}, k_{it}) + \gamma_{it} \quad (5)$$

where $\varphi(Inv_{it}, k_{it}) = \beta_0 + \beta_l k_{it} + h(Inv_{it}, k_{it})$. In Olley and Pakes (1996), the function $\varphi(\cdot)$ is approximated using a third-order polynomial in capital stock and investment. Since the unobserved productivity shock is controlled for in equation (5), the OLS estimates of the labour input coefficient β_l are consistent. To recover the β_k coefficient for the capital stock, a second step is estimated, consisting of the estimation of a probit to model survival probability of the firm and a NNLS regression that resembles the selection correction using the IMR (see Olley and Pakes, 1996, for details). Standard errors are obtained using clustered bootstrapping[26]. Productivity is computed as (Olley and Pakes, 1996): $ln(TFP)_{it} = y_{it} - \beta_l * l_{it} - \beta_k * k_{it} - (\sum_{d=2}^{D} \beta_d D)$. The approach described is estimated for each sector broad section, including country specific dummies as controls in the production function.

An alternative method to correct for endogeneity is proposed in Levinsohn and Petrin (2003). They proposed a similar approach, but using an alternative proxy that overcomes the issue that in typical firm-level datasets, firm investment is characterized by the presence of a large number of zero values, as well as being lumpy in nature. Instead, they proposed firm intermediate input (II_{it}) value as the proxy for a_{it}. Intermediate inputs also are easier to adjust in practice for firms, when compared to investment; therefore, the assumption that firms would adjust their production decisions to productivity shocks known to them is more realistic. In this case, the productivity shock is proxied using the following function (analogous to equation (4)):

$$a_{it} = h(II_{it}, k_{it}) \quad (6)$$

Again, replacing equation (6) into (3), we obtain:

[26] The Ackerberg, Caves and Frazer (2015) correction was applied in an alternative set of estimates, with unsatisfactory results.

$$y_{it} = \beta_1 l_{it} + \varphi(II_{it}, k_{it}) + \gamma_{it} \tag{7}$$

where $\varphi(II_{it}, k_{it}) = \beta_0 + \beta_l k_{it} + h(II_{it}, k_{it})$, and $\varphi(\cdot)$ is approximated using a third-order polynomial. Again, this method relies on a two-step estimation approach, however as opposed to NNLS in the previous approach; the estimation of the production function is achieved using GMM.

Appendix 4 – Additional robustness checks

Table A4.1. Alternative productivity measures and estimation approaches

	(1) Labour prod.	(2) OLS	(3) FE	(4) OP(96)	(5) IV regression
Treat*Post	-0.081***	-0.078***	-0.073***	-0.075***	-1.889***
	(0.028)	(0.027)	(0.026)	(0.026)	(0.257)
ln(Total Assets)$_{t-1}$	-0.038	-0.100	0.007	-0.031	0.127***
	(0.074)	(0.077)	(0.078)	(0.075)	(0.003)
ln(Fixed Assets/Total Assets)$_{t-1}$	-0.451	-1.079**	-0.663	-0.744*	-0.142***
	(0.497)	(0.499)	(0.422)	(0.452)	(0.010)
ln(Loans/Total Assets)$_{t-1}$	-0.114	-0.054	-0.020	-0.042	-0.006
	(0.220)	(0.221)	(0.212)	(0.214)	(0.008)
ln(Op. costs/Turnover)$_{t-1}$	-1.692***	-1.742***	-1.722***	-1.698***	-0.241***
	(0.354)	(0.351)	(0.358)	(0.352)	(0.033)
ln(Profits/Total Assets)$_{t-1}$	-0.026	0.020	0.033	0.017	0.335***
	(0.157)	(0.159)	(0.154)	(0.155)	(0.019)
Observations	1,375,295	1,375,295	1,375,295	1,375,295	1,292,437
R-squared	0.809	0.852	0.836	0.872	-
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are: (1) Partial productivity of labour (no. employees/value added); (2) TFP measure computed as the residual of an OLS estimation of the production function in equation (2); (3) TFP measure computed as the residual of a FE estimation of the production function in equation (2); (4) TFP measure computed using the Olley and Pakes (1996) approach.