European Commission

JRC TECHNICAL REPORT

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

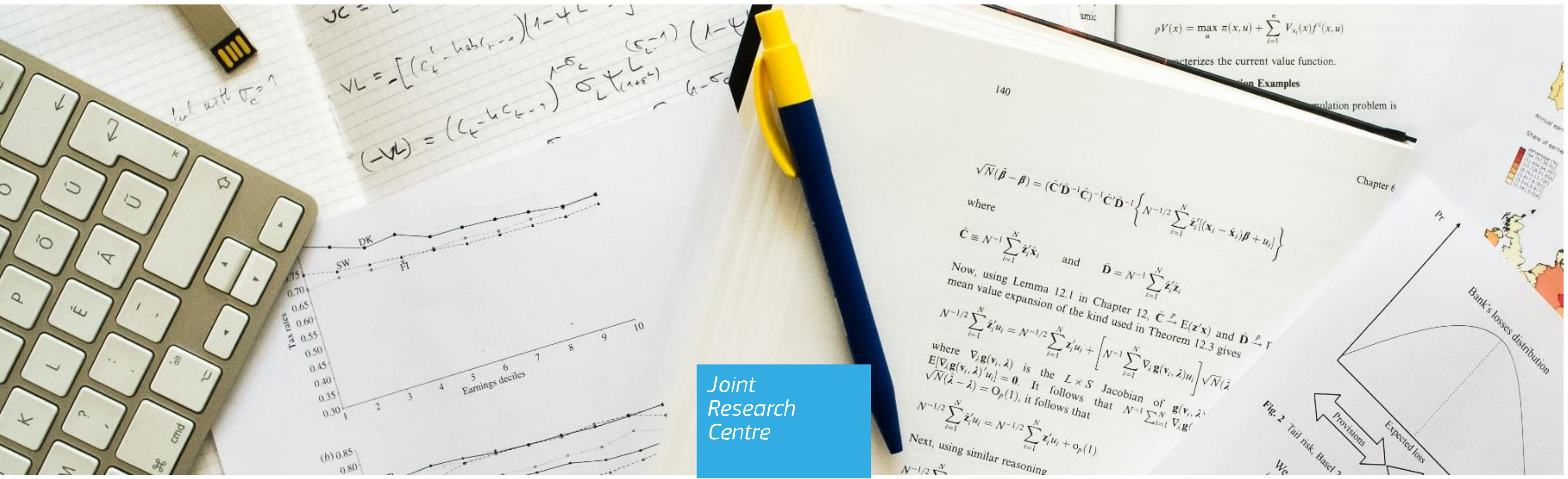
Gregori, Wildmer Daniel

Martinez Cillero, Maria

Nardo, Michela

2021

JRC Working Papers in Economics and Finance, 2021/6



Joint Research Centre

Contact information
Name: Maria Martinez Cillero
Address: via Enrico Fermi, 2749, Ispra (VA), Italy.
Email: Maria.MARTINEZ-CILLERO@ec.europa.eu

EU Science Hub
https://ec.europa.eu/jrc

JRC125470

Ispra: European Commission, 2021.

How to cite this report: Gregori, W. D., Martinez Cillero, M., & Nardo, M. (2021). The effects of cross-border acquisitions on firms' productivity in the EU, European Commission, Ispra, JRC125470.

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

Wildmer Daniel Gregori, Maria Martinez Cillero, Michela Nardo*

(this version: June 2021)

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 Score Matching 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 and services sectors, as well as in less knowledge intensive activities. Firms targeted by acquirers originating in emerging market economies also decrease productivity of high-tech target firms.

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

JEL codes: D24, F23, F60, G34.

*Wildmer Daniel Gregori, Joint Research Centre, European Commission, Via Enrico Fermi 2749, 21027 Ispra, Italy; email: wildmer.gregori@ec.europa.eu. Maria Martinez Cillero, Joint Research Centre, European Commission, Via Enrico Fermi 2749, 21027 Ispra, Italy, email: maria.martinez-cillero@ec.europa.eu. Michela Nardo, Joint Research Centre, European Commission, Via Enrico Fermi 2749, 21027 Ispra, Italy, email: michela.nardo@ec.europa.eu. We would like to thank Andrea Bellucci, Silvia Caló, Fabio Di Dio and Filippo Pericoli for insightful comments and suggestions. We would also like to thank participants at the European Commission - Joint Research Centre seminar (Ispra - Italy, 2021) Responsibility for any errors lies solely with the authors. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

Non-technical summary

This paper analyses the effects of cross-border acquisitions on the productivity of acquired firms. The issue touches upon the heart of the link between foreign investments and domestic growth as the traditional view see productivity improvement in acquired firms as driven by superior production technology or intangible assets owned by the foreign acquiring firm. In the past years, however, the European countries present an average productivity growth lower than 1%, underperforming the average of OECD countries in most cases.In this framework, productivity enhancing FDI could palliate the persistency of low productivity growth in Europe, well documented in the economics literature, thereby positively affecting citizens' living standards.

The increase in productivity, in practice, is largely dependent on factors such as the sector target firms operate in (such as vertical vs horizontal acquisition, spillover effects) or firm level characteristics (such as 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 Foreign Direct Investments (FDI) and firm competitiveness. The positive link between FDI and growth is, therefore, a "less controversial hypothesis in theory than in practice" (De Mello, 1999) and the literature supplies contrasting empirical results.

Yet, the question is of policy relevance, as EU countries are among the most open economies for FDI worldwide although in the last years a decline in FDIs has been observed together with the reshaping of international supply chains and fostered by geopolitical considerations. The pandemics amplified the push for reshoring key industries in US and Europe fuelled by the disruption of global value chains. In the COVID-19 year, FDI flows into EU fell drastically to €94bn, down from €315bn in 2019 marking a -79% when compared to the peak year 2018. In 2020 inward FDI accounted for a meagre 0.74% of EU27 GDP, down from 4% in 2015.[1]

The main questions addressed in this paper are the following: what happens to target EU companies when they are taken over by non-EU investors? Does ex-post productivity of acquired companies differ compared to non-acquired ones? Are there sectoral differences?

[1] See: https://www.oecd.org/daf/inv/investment-policy/statistics.htm.

Using Bureau van Dijk's firm level information on cross-border acquisition deals in EU28 and the ownership structures of the investing companies, we find during the years 2008-2018[2] that cross-border acquisitions decreased by over 4% the productivity level of the acquired EU firm. This effect is particularly strong and significant in the year of the acquisition reaching -5.7% and still present in the 3 years immediately after it, rounding -4.5%.

The literature has pointed to difficulties incorporating the acquired firm in the operations and structure of the investor, leading to managerial dis-synergies that negatively affect productivity. The lack of productivity improvements observed post-acquisition might be also linked to the acquired firms being more productive than the foreign investors. In this context, it could be the case that the assets (especially Intellectually Property rights) of the acquired firms are being transferred to the investor leading to downgrading of European firms' production capabilities. It is likely that this behaviour could be linked to specificities relating to the sector or the country of origin of the acquiring firm.

A more granular analysis on our sample highlights that the effects of acquisitions are concentrated in three out of the nine sectors included. For acquisitions in the manufacturing and services sectors, the effect is negative and statistically significant as in the general case, with a decrease in productivity post acquisition close to 6.8% and 4% respectively. This is particularly relevant because these two sectors together represent the majority of acquisitions implemented during the years 2008-2018, with about 60% of all deals. Foreign acquisitions in the construction sector have a positive and statistically significant effects on firm level productivity, in contrast with the general case, also because this sector counts for less than 4% of all acquisitions deals. Despite the lack of statistically significance in the remaining sectors, the coefficients are negative in all cases.

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 a foreign acquisition on firm level productivity. We explore this feature in manufacturing and services sectors by distinguishing according to the degree of technological development or knowledge intensity of the activities carried out by manufacturing and services target firms, respectively. We find that the effect of cross-border acquisitions on productivity of the target firm is again negative and statistically significant no matter the degree of technological development in the manufacturing sector, the magnitude laying between -6.6%

[2] 2019 and 2020 data are available only for the detailed M&As deals but not for the ownership structure of companies, which, at the time of the analysis, was fully available only until 2018. This constraints the time window of the data available for the quantitative analysis.

and -7%, while this result holds only for less knowledge intensive services sectors with an effect close to -4.6%. In contrast, cross-border acquisitions that occurred in the knowledge intensive services' sectors have a statistically insignificant effect on the productivity of the targeted firms. The productivity reductions observed in the less knowledge or technology intensive sectors post acquisitions, could be due to the fact that these sectors are mainly targeted by acquiring firms originating in emerging or developing economies, thus characterised by lower productivity, that may negatively influence productivity of the target firms.

To explore if the country of origin of the acquiring firm helps identifying potential pervasive effects of foreign acquisitions on productivity of the target firm, we classify each investor according to the location of its ultimate owner. We identify five geographical regions: EU, US, emerging economies, Offshore Financial Centres (OFCs), and Rest of the World (RoW). Emerging economies include, among others, China, India, Russia, Turkey and Middle East countries. RoW includes Switzerland, Rep. of Korea and Japan among others. We find that when the investor ultimately comes from US the productivity of the target firm does not change, no matter the sector of the target company. This is good news as US is the main foreign investor in the EU, representing about 46% of all non-EU foreign acquisition deals made in EU in our time span. Instead, when ultimate owners come from another EU country, the effect on productivity post acquisition is negative, reaching -5.6%.

When acquiring firms have an ultimate owner originating in emerging economies, the productivity of target firms is affected negatively, with the negative effect close to -11.4% and being statistically significant only for acquisitions that take place in high technology manufacturing or knowledge intensive services. This suggests a drain of knowledge from the target company to the investor, that should be further investigated with patents data. By contrast, acquisitions involving acquiring firms with ultimate owners in both OFCs and RoW have a negative effect on the productivity of the target firm (-16.8% and -7.8% respectively), both restricted to acquisitions in less knowledge intensive/low technology sectors. The magnitude of this negative effect is noticeably higher for OFCs, possibly indicating that acquiring firms involved in these acquisitions are exporting lower productivity to the target firms. As final remark, an emerging topic in the foreign acquisitions literature relates to the type of entity of the acquirer, or its ultimate owner, and in particular whether they are state owned or state controlled enterprises. Therefore, further analysis exploring the status of the acquiring firm could provide useful empirical evidence, and it is left for future work.

1. Introduction

The persistency of low productivity growth has been well documented in the economics literature and it is a relevant issue as it affects citizens' living standards.[3] Figure 1 illustrates the annual productivity growth in the European Union and among OECD countries between 2008 and 2018. While the low productivity issue is common to all of them, in the last years the European countries present an average growth lower than 1%, underperforming the average of OECD countries in most cases. There could be different reasons behind 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). 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.

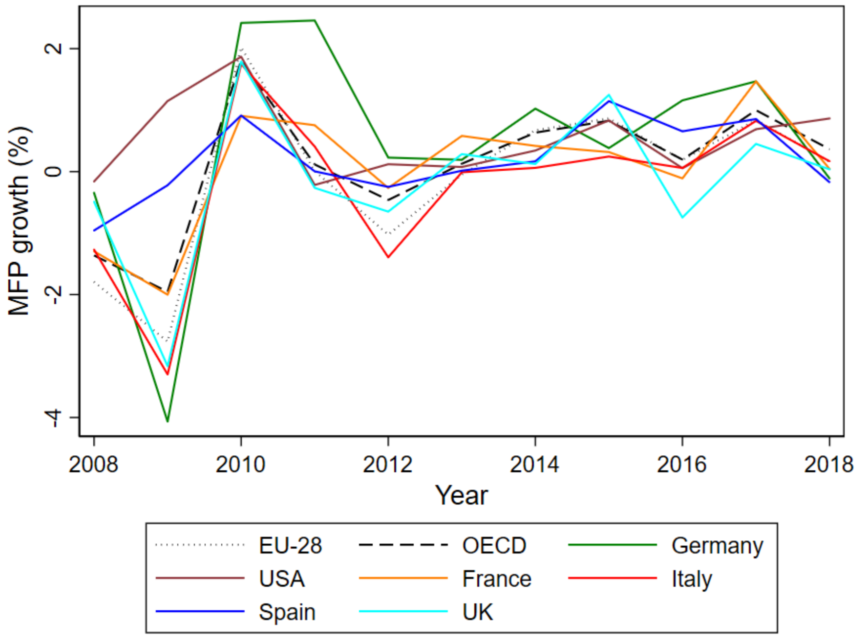
In addition to the persistent European low productivity, the current political debate, exacerbated by the Covid-19 crisis, often focuses on foreign acquisitions, due to the fear of potential threats for the European sovereignty, in particular when foreign takeovers target firms in strategic sectors. 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.*"[4] In this regard, the EU has recently adopted a new Regulation on

[3] 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.

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

foreign direct investment screening, on the ground of security and public order, which has been operational since October 2020.

Figure 1. Multifactor productivity growth



Source: Authors' calculations, based on OECD Multifactor productivity data.

In this context, our analysis related to the effects of cross-border acquisitions on productivity may provide useful insights to feed the political discussion. The main questions we intend to address are the following: what happens to target EU[5] 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 firms' productivity, comparing acquired firms with those companies that have not been acquired. Our identification strategy relies on the Propensity Score Matching (PSM), useful to identify the 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-

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

border acquisitions decrease the productivity level of the acquired firm, especially in manufacturing and services sectors, as well as in less knowledge intensive activities.

The contribution of our study to the literature is twofold. Firstly, it adds to the strand of the literature that investigates the relationship between foreign direct investment (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 based on Lithuanian manufacturing firm-level data. Results showed that there are 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 showing that there was not a solid evidence of long-run effects of foreign ownership on TFP at the aggregate level, but there was heterogeneity across sectors and contrasting results in relation to short vs 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 capitals and institutions is taken into account. Differently from previous studies, our study provides new evidence of negative effects of inward cross-border acquisitions on TFP in the European Union, disentangling heterogeneity across sectors with a special focus on knowledge vs less knowledge intensive activities. 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. Some papers have recently explored productivity differentials between affiliates emerging market foreign firms operating in the EU, when compared to affiliates of developed markets foreign firms, in several sectors. Pittiglio and Reganati (2018) highlight the importance of accounting for the type and motivations behind FDI, as it affects performance of foreign owned firms in the EU. Sanfilippo (2015) also uncovers lower productivity differential of emerging economies foreign owned firms, and noted that the differential was larger in more sophisticated manufacturing and services activities and when this type of FDI is targeted to Western European countries. Sanfilippo (2015) finds productivity gaps between emerging and advanced economies foreign owned firms, and concluded that European affiliates owned by parents located in foreign emerging economies were less productive. We however try and establish a causal link between the foreign acquisition and the productivity differential pre- and post-acquisition that is directly attributable to the acquisition. Related analysis to ours can be found for example in Carril-Caccia (2020), who studies the case of cross-border M&As in the French manufacturing sector, without finding significant effects on TFP when M&As are implemented by developed or emerging countries. However, there is an increase in the acquired firms' TFP when the M&As is done by European countries, but only in the long term. We extend these analyses by including more countries and exploiting a wider sector categorisation.

In addition, this study contributes to the strand of the literature which implements PSM combined with DiD techniques to study the effects of FDIs. In fact, since the seminal papers of Rosenbaum and Rubin (1983) and Heckman et al. (1997), to overcome the issue of self-selection bias the combination of PSM and DiD has been widely implement also in the FDI literature. 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) highlight that FDI are more attracted by those developing countries with stables exchange rates relative to those countries with more flexibles exchange rates. In relation to causal effect of FDI on total factor productivity, among other also Schiffbauer et al. (2017) and Carril-Caccia (2020) also rely on the combination of PSM and DiD. Our analysis is based on this identification strategy, but we also exploit the recent contributions made by Athey and Imbens (2018) and Callaway and Sant'Anna (2020). They suggest an approach to estimate the DiD model in a setting of panel data, called a staggered DiD, to identify causal treatment effects. Thus, we combine the PSM with the staggered DiD approach 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 how well (or not) they combine inputs 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, thus 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 though the transfer of superior managerial practices or capabilities (Bertrand and Zitouna, 2008). The successful transfer of these practices would translate into technical efficiency improvements at the firm level, which leads to improved productivity in the target firm. Finally, a cross-border acquisition may also affect firm productivity through 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), finding 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 this theoretical postulates, empirical literature in the area has found inconclusive evidence regarding the effects of cross-border acquisitions (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).[6] Moreover, there are several reasons why a positive impact of a cross-border acquisition 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. First, negative effects on productivity can result from a cross-border takeover if it causes dis-synergies (Buckley et al., 2014), which

[6] Domestic acquisitions are not the topic of this analysis and the discussion of these affects are left out of this review.

occur when the acquiring and target firms possess stocks of knowledge capital that are not complementary. Moreover, it could simply 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 an appropriate training of the staff, in the newly acquired firm are present (Djankov and Hoekman, 2000; Keller, 2004). Therefore, in case that the technology is not well exploited, it might explain lower TFP post-acquisition. In modern cross-border acquisitions, knowledge intensive assets have become increasingly prevalent. The effective transmission of this specific type of 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 know-how from the acquired firm, rather than the other way around (Dunning, 1998; Salis, 2008; Dunning, 2009), particularly in certain specific sectors. For example, in manufacturing the phenomenon of asset-seeking in FDI is rather prevalent, which would result in a reverse flow of assets from the acquired firm to the acquiring company instead. 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 particularly the case with acquisitions where the acquiring firm originates in an emerging economy. In these cases, the theoretical mechanisms that suggest productivity improvements though technology or managerial transfers is less clear (Chari et al., 2012; Buckley et al, 2014; Pittiglio and Reganati, 2018). These type of acquiring firm 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 effects of a cross-border acquisition on productivity could be linked to difficulties when incorporating the acquired firm in the structure of the acquiring 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 firms' 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 as a result 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 and/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, starting from the illustration of the identification strategy.

3. Identification strategy

Our goal is to study 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 DiD estimator. In this setting, and in order to identify the causal effect 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 is composed by those firms that have been acquired. The control group is composed by those firms that have never been acquired. An important feature of our treatment, 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 latter aspect, 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 the acquisition in a setting of 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 stablishing the proper comparison group in order to assess the productivity of acquired firms post-acquisition difficult. Second, an issue with endogeneity can arise due to the fact that 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 Propensity Score Matching

In order to overcome the aforementioned biases, before estimating the DiD regression, we apply PSM. PSM is designed to reduce the selection bias by providing a comparable control group based on the propensity score (PS), 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 (we will come back to the relevance of this aspect for our estimation approach in the next sub-section). In order to obtain the PS, we implement PSM using nearest-neighbour matching.[7] Afterwards, we use the estimated PS to re-weight the observations in the sample.[8] This way, observations in the control group are weighted to be similar (comparable) to those in the target group. This approach was suggested by Hirano and Imbens (2002) and Hirano et al. (2003), and it has been implemented in related empirical analyses by Mu and van de Walle (2011), Chari et al. (2012) or Cozza et al. (2015), among others. These analyses estimated a PS-weighted DiD equation. However, in our estimation approach, we implement a staggered DiD instead, which will be described in the next section. For firms in the target group, the assigned weight ω_{it} is equal to 1, while for firms in the control group the assigned weight is calculated as $\omega_{it} = PS_{it}/(1 - PS_{it})$. We refer the reader to Caliendo and Kopeinig (2008) and Khandker et al. (2010) for further details on the re-weighting DiD approach.

3.2. Identification of the treatment effect

While PSM corrects for 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

[7] We use the Stata command *psmatch2* in our analysis (Leuven and Sianesi, 2003). We estimated a logit regression in order to model the probability of firms being acquired, including target firms on the year immediately before the acquisition happened, in order to match them to firms in the control group that share similar firm characteristics pre-acquisition. We assess the robustness of these choices in Section 6.

[8] In addition to this re-weighting, we impose a common support by dropping treated firms whose PS is higher than the maximum or less than the minimum propensity score of the treated group. PSM is successful when the common support condition is satisfied, as it makes surer that firms with the same characteristics (as defined in the set of control variables included in the PSM estimation) have positive probability of being treated and not treated (Caliendo and Kopeinig, 2008).

second set of biases, a DiD estimator is used. In this case, we implement (PS-weighted) staggered DiD, specified as follows:

$$Y_{it} = \alpha_0 + \alpha_1 W_{it} + \boldsymbol{\beta X_{it-1}} + \boldsymbol{\gamma Z_{ct-1}} + \varphi_i + \sigma_t + \epsilon_{it} \quad (1)$$

where Y_{it} is the log of TFP of firm i at time t. W_{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).[9] Also included in equation (1) is $\boldsymbol{X_{it-1}}$, which denotes a vector of controls which 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. $\boldsymbol{Z_{ct-1}}$ is a vector of macroeconomic factors at the country level 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. φ_i are firms' fixed effects, to control for time-invariant characteristics at the firm level. We also 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.

[9] 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 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.

4. Dataset

We use Orbis financial, sectoral classification (NACE Rev. 2) and legal data compiled and provided by Bureau van Dijk (BvD), for the period 2005 to 2018.[10] 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 5 employees.[11] 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. 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 plus UK, which we refer to as foreign investors. We select completed and confirmed deals. Several selection steps were carried out to this original sample of deals.[12] After the data cleaning process in each database, Zephyr acquisitions data is merged with the selected Orbis financial information.[13] Through this merging, the treated and control firm groups in each country are identified. Some cleaning criteria are applied to the control firms group, in order to improve comparability and finding a match for the treated firms. 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.

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

[10] We excluded data corresponding to the years 2019 and 2020 due to it being incomplete, and data corresponding to the years prior to 2005 because the number of available observations wad significantly lower than those available in the time period selected.

[11] We selected unconsolidated accounts, except for firms which only reported consolidated accounts. We assess the robustness of the results to this selection choice in Section 6.

[12] 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.

[13] We use the BvD ID variable in Zephyr and the corresponding BvD ID variable in the Orbis financial dataset.

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)[14] 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, this does 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, and the resulting estimated Solow's residuals:

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

Equation (2) displays a Cobb-Douglas production function, where y_{it} is firm total output, l_{it} is the labour (variable) input, and 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 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 (2003) estimation

[14] 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.

approach.[15] This and alternative TFP estimation approaches, which we will use to assess the robustness of our results, 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.[16] 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: operating revenue – (imputed) value added.[17]

The firm level characteristics included as controls in the staggered DiD regression are also based on Orbis and Zephyr data. The treatment dummy (W_{it}) 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 threated firms, from the acquisitions' year onwards, and zero for treated firms' pre-acquisitions and also for control firms). An additional set of firms' level control variables are taken from Orbis, being 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). The macro-economic indicators also included as controls 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.[18] Table 1 displays descriptive statistics for the main variables included in the empirical model, for the control group and the target group. Target firms are substantially higher on average than those in the control group in terms of the value of total assets. The average proportion of fixed assets on total assets however is smaller for target firms. Target firms have on the average lower value of loans over total assets and lower operational costs relative to turnover, compared to the control group. Target firms however 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.

---

[15] The production function in equation (2) is estimated for each country and each NACE Rev. 2 broad sector category (i.e. one-digit) separately.
[16] 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 value added observations internally using "cost of employees + EBITDA".
[17] All monetary values are deflated using sector and country specific price indices taken from the Klems database.
[18] Austria, Belgium, Germany, Denmark, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the UK. Although previously included in the cleaned Zephyr extraction, Greece did not have enough observations to compute TFP which could be used in subsequent analysis.

Table 1. Descriptive statistics

	Observations	Mean	Std. Dev.	Minimum	Maximum	Median
Control sample						
ln(TFP)	2,122,381	11.343	0.690	3.416	20.349	11.284
Total assets	2,122,381	36.664	1,415.142	1.000	506,365.440	3.476
Fixed Assets/Total Assets	2,122,381	0.245	0.239	0	1.000	0.167
Loans/Total Assets	2,122,381	0.090	0.133	0	16.968	0.031
Profits/Total Assets	2,122,381	0.073	1.157	0	1,681.542	0.046
Op. costs/Turnover	2,122,381	0.929	0.084	0	1	0.956
Target sample						
ln(TFP)	19,403	12.062	0.894	8.363	19.339	11.897
Total assets	19,403	1,685.630	24,455.389	1.000	1,569,502.500	24.414
Fixed Assets/Total Assets	19,403	0.170	0.191	0	0.981	0.096
Loans/Total Assets	19,403	0.080	0.227	0	20.004	0.023
Profits/Total Assets	19,403	0.112	0.124	0	2.273	0.076
Op. costs/Turnover	19,403	0.891	0.122	0.010	1	0.929

Notes: The value of total assets is expressed in €1,000,000. "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 as part of the PSM exercise are provided in Appendix 2.[19] The positive coefficient of the log of TFP variable indicates that, within a given industry and country, acquirers prefer target firms that operate with higher productivity levels. 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 large and old target firms, although the negative sign of the squared terms of these two variables indicate that the probability of being acquired is reduced as firms become larger and older above a certain threshold. Higher cost of production with respect to firm assets also have a positive effect on the probability of being

[19] In Appendix 2 we also provide the results obtained for the balancing tests that assess the quality of the matching process.

acquired. On the other hand, having higher leverage levels and obtaining less profit per unit of asset have a negative impact on the probability of being acquired.

5.2 Baseline analysis

Table 2 displays the coefficients obtained after estimating equation (1) pooling all the data, for all countries and sectors, in our sample. The estimates in specification (3) correspond to our baseline model, which includes the full set of controls $\boldsymbol{X_{it-1}}$ and $\boldsymbol{Z_{ct-1}}$ 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) - (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 W_{it}, as shown in equation (1).

Table 2. Baseline analysis

	(1)	(2)	(3)	(4) t_0	(5) t+1	(6) t+2	(7) t+3
Treat*Post	-0.043***	-0.043***	-0.041***	-0.057***	-0.049***	-0.044***	-0.045***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)
$\ln(\text{Total Assets})_{t-1}$	0.111***	0.095***	0.098***	0.103***	0.094***	0.100***	0.101***
	(0.014)	(0.013)	(0.013)	(0.024)	(0.020)	(0.017)	(0.016)
$\ln(\text{Fixed Assets/Total Assets})_{t-1}$		-0.467***	-0.459***	-0.259***	-0.313***	-0.315***	-0.392***
		(0.085)	(0.085)	(0.097)	(0.089)	(0.085)	(0.087)
$\ln(\text{Loans/Total Assets})_{t-1}$		0.067	0.075	0.061	0.058	0.039	0.052
		(0.064)	(0.064)	(0.080)	(0.075)	(0.068)	(0.069)
$\ln(\text{Op. costs/Turnover})_{t-1}$		-0.231***	-0.228***	-0.131	-0.188**	-0.195**	-0.214**
		(0.085)	(0.084)	(0.098)	(0.096)	(0.093)	(0.090)
$\ln(\text{Profits/Total Assets})_{t-1}$		0.366***	0.367***	0.218***	0.208***	0.267***	0.296***
		(0.053)	(0.053)	(0.056)	(0.060)	(0.058)	(0.057)
Inflation_{t-1}			-1.148*	-1.743**	-1.312**	-1.575**	-1.612**
			(0.639)	(0.682)	(0.669)	(0.672)	(0.662)
$\ln(\text{PerCapitaGDP})_{t-1}$			-0.194**	-0.258***	-0.150	-0.165*	-0.145
			(0.086)	(0.098)	(0.100)	(0.092)	(0.095)
Observations	2,022,711	2,022,654	2,022,654	2,013,678	2,016,316	2,018,241	2,019,671
R-squared	0.838	0.841	0.841	0.861	0.856	0.848	0.842
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Robust standard errors in parentheses. *** 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 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 productivity is positively related with total assets and with the profitability ratio. For total assets, the positive sign could be linked to bigger firms being able to exploit factors such as economies of scales, therefore leading to a higher TFP. The positive effect of returns on assets could be linked to more productive activities (or using a more efficient and innovative production technology) carried out by the firm. 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. Having a higher proportion of total assets in the form of fixed assets is negatively linked to TFP, suggesting that a relative lower level of long-term tangible assets such as property, plants and equipment foster productivity, thanks to a higher relative level of intangibles (i.e. Research and Development), and current assets, more liquid, better able to foster innovation and adapt to sudden change in market conditions. Finally, indebtedness does not have a statistically significant effect on TFP.

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.[20] Specifications (4) to (7) in Table 2 display the regression coefficients obtained though this exercise. All the post-treatment coefficients are again negative and statistically significant at the 1% level. The magnitude of these coefficients however is larger than that of the coefficient in the baseline model, particularly in the year of the acquisition and in the year immediately after it. Different time effects post-acquisition have been identified in the literature before, for example in Schiffbauer et al. (2017) or Salis (2008). The larger negative impact in the years closer to the acquisition is likely to be linked to reorganization costs in the short run (Schiffbauer et al., 2017), or to initial assimilation problems immediately after the acquisition took place (Salis, 2008).

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 treated and control firms operate. The results of the sector specific estimations are displayed in Table 3.

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 construction sector have a positive and statistically significant effects on firm level productivity, while for the case of acquisitions in the manufacturing and services sectors, the effect is also statistically significant but negative. Despite the lack of statistically significance at the 10% level of the treatment coefficients in the remaining sectors, the coefficients are also negative in all cases. Where statistically significant, the coefficients obtained for the firm specific characteristics included as controls in the staggered DiD regression have the same signs as those estimated in the pooled baseline model.

[20] 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. 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	-0.030	-0.068***	-0.023	0.153*	-0.040*	-0.008	-0.009	-0.012	-0.050
	(0.101)	(0.017)	(0.109)	(0.090)	(0.022)	(0.033)	(0.082)	(0.124)	(0.038)
ln(Total Assets)$_{t-1}$	0.006	0.073***	0.065	0.118*	0.145***	0.074**	0.242***	0.178	0.055
	(0.174)	(0.020)	(0.110)	(0.069)	(0.028)	(0.031)	(0.064)	(0.175)	(0.040)
ln(Fixed Assets/Total Assets)$_{t-1}$	0.568	-0.768***	-0.208	-0.202	-0.199	-0.207	0.176	-0.246	-0.610**
	(0.889)	(0.118)	(0.397)	(0.370)	(0.170)	(0.312)	(0.452)	(0.443)	(0.250)
ln(Loans/Total Assets)$_{t-1}$	0.001	0.074	-0.506*	-0.352	0.084	0.101	0.200	0.684	0.168
	(0.365)	(0.081)	(0.300)	(0.422)	(0.165)	(0.168)	(0.302)	(0.687)	(0.181)
ln(Op. costs/Turnover)$_{t-1}$	-0.266	-0.284	0.058	-0.702	-0.762***	-0.198	0.214	-0.747*	-0.130
	(0.332)	(0.187)	(0.198)	(0.844)	(0.252)	(0.164)	(0.157)	(0.448)	(0.158)
ln(Profits/Total Assets)$_{t-1}$	0.341	0.528***	0.347	0.288	0.518***	0.098	0.453***	0.429	0.267***
	(0.402)	(0.099)	(0.694)	(0.308)	(0.129)	(0.083)	(0.161)	(0.389)	(0.089)
Inflation$_{t-1}$	-9.350	-0.490	7.790*	0.791	-2.383*	-3.993**	-4.899	8.818	-1.055
	(6.870)	(0.899)	(4.239)	(4.238)	(1.253)	(1.709)	(3.821)	(5.954)	(2.072)
ln(PerCapitaGDP)$_{t-1}$	-1.973***	0.066	-0.428	-0.350	-0.277*	-0.124	-0.960*	-1.929**	-0.151
	(0.746)	(0.127)	(0.690)	(0.545)	(0.167)	(0.220)	(0.579)	(0.972)	(0.224)
Observations	54,835	672,041	49,752	212,797	770,699	69,645	30,955	57,193	104,737
R-squared	0.910	0.807	0.884	0.837	0.801	0.790	0.856	0.829	0.764
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is log(TFP). Robust 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 3, it is worth exploring in more detail cross-border acquisitions in the manufacturing and services sectors, as these broadly defined sector categories are characterised by the large heterogeneity of firms they include,[21] in terms of aspects such as specialisation or technology innovation. 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. 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.

We exploit Eurostat classification based on technological intensity and 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).[22] 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 R&D expenditure/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.[23] Again, we estimate our baseline staggered DiD regression for each of these four alternative sectoral groupings of manufacturing and services firms, and provide the estimates in Table 4.

The effect of cross-border acquisitions on the TFP of the target firm 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 4. Previous empirical research on cross-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

[21] 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 categories for services and manufacturing (tables available upon request from the authors).

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

[23] 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

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 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).

Table 4. 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	-0.066***	-0.070***	-0.014	-0.046**
	(0.023)	(0.024)	(0.025)	(0.023)
$\ln(\text{Total Assets})_{t-1}$	0.058**	0.083***	0.094***	0.138***
	(0.027)	(0.031)	(0.023)	(0.028)
$\ln(\text{Fixed Assets/Total Assets})_{t-1}$	-0.785***	-0.759***	-0.223	-0.229
	(0.137)	(0.180)	(0.203)	(0.166)
$\ln(\text{Loans/Total Assets})_{t-1}$	0.046	0.105	0.207*	0.074
	(0.090)	(0.144)	(0.120)	(0.165)
$\ln(\text{Op. costs/Turnover})_{t-1}$	-0.522***	0.023	-0.067	-0.775***
	(0.199)	(0.329)	(0.092)	(0.217)
$\ln(\text{Profits/Total Assets})_{t-1}$	0.364***	0.768***	0.211***	0.471***
	(0.100)	(0.184)	(0.066)	(0.124)
Inflation_{t-1}	-1.601	0.652	-2.689**	-2.259*
	(1.309)	(1.246)	(1.280)	(1.239)
$\ln(\text{PerCapitaGDP})_{t-1}$	0.060	0.082	-0.288*	-0.345**
	(0.195)	(0.161)	(0.155)	(0.171)
Observations	175,906	496,135	211,209	833,283
R-squared	0.817	0.795	0.850	0.810
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

The effect of cross-border acquisitions on acquired firms' TFP is also negative and statistically significant for the case of acquisitions that took place in less knowledge intensive services sectors (specification (4) in Table 4). In contrast, cross-border acquisitions that occurred in the knowledge intensive services' sectors have a statistically insignificant effect on the TFP of the targeted firms (specification (3) in Table 4). The productivity reductions observed in the less knowledge or technology intensive sectors post acquisitions, could be due to the fact that these sectors are mainly targeted by acquiring firms originating in emerging or developing economies, thus characterised by lower productivity, that may negatively influence productivity of the target firms.

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 foreign acquisitions on productivity of the target firm. In this analysis, we go one step forward 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[24]).

In order to explore whether the negative effects we have identified in previous sections present variation once we account for the GUO's origin, we classify acquiring firms according to the country of origin of their GUO in four geographical regions: US, emerging economies,[25] Offshore Financial Centres (OFCs)[26], and Rest of the World (RoW). Acquisitions where the GUO originates in the US represent 24 per cent of the total number of acquisitions in our data, while the percentages for emerging economies, OFCs and RoW are 5.3, 2 and 14 percent, respectively. In order to also account for sectoral variation, we estimate separated regressions, within each of the four GUO origin categories, for knowledge intensive/high technology activities (merging specifications 1 and 3 in Table 4), and less knowledge

[24] Defined in Orbis as the global ultimate owner located anywhere in the world, but with a minimum of 50.01% share ownership.

[25] 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, South Africa.

[26] The countries included in this category are: Andorra, Barbados, Bermuda, the Bahamas, Gibraltar, the Cayman Islands, Liechtenstein, Monaco, Marshall Islands, Panama, Virgin Islands (British).

intensive/low technology activities (merging specifications 2 and 4 in Table 4) separately. Results for these estimations are provided in Table 5.

Table 5. Knowledge vs less-knowledge insensitive activities by acquirer's country of origin

	US		Emerging economies		Offshore Finc. Centres		RoW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High tech. Mnf./K.I. Serv.	Low tech. Mnf./L.K.I. Serv.	High tech. Mnf./K.I. Serv.	Low tech. Mnf./L.K.I. Serv.	High tech. Mnf./K.I. Serv.	Low tech. Mnf./L.K.I. Serv.	High tech. Mnf./K.I. Serv.	Low tech. Mnf./L.K.I. Serv.
Treat*Post	0.008	0.036	-0.114*	-0.045	-0.024	-0.168**	-0.042	-0.078**
	(0.033)	(0.046)	(0.064)	(0.052)	(0.100)	(0.082)	(0.040)	(0.039)
ln(Total Assets)$_{t-1}$	0.077***	0.061	0.057*	0.105**	0.128***	0.095***	0.103***	0.076
	(0.029)	(0.042)	(0.032)	(0.043)	(0.032)	(0.017)	(0.037)	(0.049)
ln(Fixed Assets/Total Assets)$_{t-1}$	-0.456*	-0.484**	-0.517**	-0.414**	-0.167	-0.166**	-0.410**	-0.216
	(0.270)	(0.242)	(0.217)	(0.200)	(0.155)	(0.078)	(0.201)	(0.289)
ln(Loans/Total Assets)$_{t-1}$	0.286***	0.177	-0.019	0.298	0.248	0.410*	0.134	-0.021
	(0.106)	(0.253)	(0.136)	(0.190)	(0.156)	(0.222)	(0.123)	(0.117)
ln(Op. costs/Turnover)$_{t-1}$	-0.112	-0.014	-0.196*	-0.744**	0.009	-0.369***	-0.013	-0.555
	(0.129)	(0.346)	(0.101)	(0.290)	(0.114)	(0.061)	(0.112)	(0.401)
ln(Profits/Total Assets)$_{t-1}$	0.279***	0.646***	0.175**	0.842***	0.359***	0.509***	0.194	0.570***
	(0.078)	(0.182)	(0.085)	(0.212)	(0.086)	(0.059)	(0.141)	(0.197)
Inflation$_{t-1}$	-0.545	0.150	0.104	-0.993	1.397	-0.120	-1.005	-2.087
	(1.342)	(1.571)	(0.984)	(1.123)	(1.377)	(0.806)	(1.491)	(1.529)
ln(PerCapitaGDP)$_{t-1}$	0.102	-0.108	0.093	0.019	0.008	0.095	-0.067	-0.023
	(0.200)	(0.205)	(0.183)	(0.242)	(0.134)	(0.089)	(0.204)	(0.228)
Observations	379,069	1,321,512	376,457	1,320,627	376,149	1,320,172	377,376	1,321,130
R-squared	0.861	0.875	0.907	0.865	0.893	0.903	0.880	0.840
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Emerging economies classification is described in footnote 24, and OFCs in footnote 25. RoW indicates Rest of the World. The acquirer's country of origin is defined using, when available, the location of the Gobal Ultimate Owner, otherwise the location of the acquirer.

Acquisitions where foreign acquiring firms have a GUO located in the US do not appear to have the same effect on TFP of the target firm as foreign acquisitions where acquiring firms have GUOs originating from emerging economies, OFCs or the RoW. The coefficient of the treatment dummy in specifications (1) and (2) in Table 5, corresponding to acquisitions with GUOs originating in the US, is positive but also statistically insignificant, regardless of the sectoral classification. However, when foreign acquiring firms with GUOs originating in emerging economies 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 or knowledge intensive services (as shown in specification 3 in Table 5).

By contrast, foreign acquisitions involving acquiring firms with GUOS that originate in both OFCs (specification 6) and RoW (specification 8) have a negative effect on the productivity of the target firm, both restricted to acquisitions in less knowledge intensive/low technology sectors. The magnitude of this negative effect is noticeably higher for specification (6), possibly indicating that acquiring firms involved in these acquisitions are exporting lower productivity to the target firms.

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 6. We include only acquirers that originate in a EU country, in order to check whether the baseline result is confirmed. Cross-border acquisitions where the acquiring firm is located in a EU country represent about 55 per cent of all acquisitions in our data. The negative and statistically significant result is still present.

Considering that we use Orbis financial data, three 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 immediately after the start of the 2008 financial crisis. As displayed in Figure 2, the TFP estimates corresponding to this 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 6. 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[27], 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. The alternative set of coefficients are displayed in Table 6 specification (3). Again, the baseline estimates appear robust to the exclusion or inclusion of micro firms in the sample. 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

[27] 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).

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 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.[28] The resulting set of coefficients are displayed in Table 6 specification (4). Again, main results are confirmed.

Table 6. Robustness on baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EU acquirers	t>2011	No micro	No Subsidiaries	Labour prod.	OLS	FE	OP(96)
Treat*Post	-0.056***	-0.044***	-0.040***	-0.053***	-0.037***	-0.036***	-0.039***	-0.039***
	(0.015)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
$\ln(\text{Total Assets})_{t-1}$	0.109***	0.058***	0.098***	0.109***	0.019	-0.025*	0.081***	0.032**
	(0.017)	(0.017)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.014)
$\ln(\text{Fixed Assets/Total Assets})_{t-1}$	-0.467***	-0.399***	-0.468***	-0.390***	-0.313***	-0.934***	-0.548***	-0.618***
	(0.093)	(0.110)	(0.086)	(0.089)	(0.099)	(0.093)	(0.085)	(0.090)
$\ln(\text{Loans/Total Assets})_{t-1}$	-0.140*	0.118	0.061	0.082	0.102	0.095	0.081	0.088
	(0.075)	(0.072)	(0.064)	(0.086)	(0.065)	(0.065)	(0.064)	(0.064)
$\ln(\text{Op. costs/Turnover})_{t-1}$	-0.230*	-0.187*	-0.209**	-0.613***	-0.174*	-0.211**	-0.230***	-0.211**
	(0.119)	(0.106)	(0.083)	(0.187)	(0.090)	(0.090)	(0.085)	(0.087)
$\ln(\text{Profits/Total Assets})_{t-1}$	0.370***	0.230***	0.367***	0.266***	0.360***	0.372***	0.367***	0.366***
	(0.063)	(0.058)	(0.053)	(0.075)	(0.055)	(0.054)	(0.052)	(0.054)
Inflation_{t-1}	-1.068	-1.143	-1.058*	-1.554**	-1.050	-1.308**	-1.150*	-1.195*
	(0.805)	(0.832)	(0.636)	(0.718)	(0.673)	(0.657)	(0.637)	(0.649)
$\ln(\text{PerCapitaGDP})_{t-1}$	-0.278***	-0.340***	-0.181**	-0.182**	-0.057	-0.114	-0.175**	-0.132
	(0.100)	(0.122)	(0.086)	(0.090)	(0.097)	(0.093)	(0.088)	(0.090)
Observations	2,012,613	1,484,156	1,776,575	1,898,736	2,022,654	2,022,654	2,022,654	2,022,654
R-squared	0.857	0.862	0.842	0.817	0.856	0.869	0.875	0.874
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Further sensitivity analyses to the methods applied in the empirical analysis presented in the previous section were also carried out (with alternative tables of estimates available from the corresponding author upon request. The first set of sensitivity analysis relate to the PSM performed in step 1 of our estimation approach. The results presented are based on nearest-neighbour PSM (using 10 neighbours). Alternatively, we tested the sensitivity of our results to the use of other possible matching methods, such

[28] Account consolidation type U1, as defined by Oribs.

as variations in the number of neighbours selected, and applying kernel, instead of nearest-neighbour, matching. We also attempted to perform the matching within years. Overall, our treatment estimates were robust to the PSM implementation, and the presented PSM results were selected in terms of the matching performance assessed based on the balancing tests. The second set of 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 Fixed Effects regressions to obtain the production function residuals. In addition, partial productivity measures, such as labour productivity, can be comported 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 6 specifications (5) to (8). 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 Screening mechanism in 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 2008-2018.

The traditional view is that productivity improvement in target firms arising from FDIs is 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 a two-step process that combines PSM with 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 include din our sample. Thus, we are able to identify cross-border acquisition's effects on the TFP of the target firms. We focus our sample of target firms on those located in 14 EU economies in the years 2008-2018.

We uncover evidence suggesting a negative and statistically significant effect of cross-border acquisitions on TFP of European firms in recent years. In contrast with our findings, previous research such as Girma and Görg (2002), Harris and Robinson (2002) or Schiffbauer et al. (2017) found also negative, but much 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, as well as to the novel staggered DiD estimation approach.

Moreover, we explore in detail variability in terms of sector of operation and country of origin of the foreign investor. 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 services sectors. For the former sector, this negative effect is found in both high-tech and low-tech targets, while for the latter one the evidence is statistically significant only for knowledge intensive sectors. Possibility, 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 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 acquiring firm GUO also appears to matter. We identify contrasting results between GUOs in the US when compared to GUOs in other economies in the less knowledge intensive services and low technology manufacturing sectors, particularly in offshore financial centers. For the case of GUOs in emerging economies, we find that the negative effect on productivity of target firms relate to knowledge intensive services and high technology manufacturing sectors, possibly indicating that acquiring firms involved in these acquisitions are exporting lower productivity.

Some limitations are present in the empirical analysis provided in this paper. It should be noted that the methodology accounts for important sources of endogeneity, such as selection bias and time-invariant unobservables (Lipsey et al., 2013). Moreover, measuring the extent to which spillovers are driving our results is challenging in the frame of our analysis. Further research could aim at disentangling potential spillover effects in the methodological framework we apply. 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 the status of the acquiring firm could provide useful empirical evidence.

References

Alfaro, L., Kalemli-Ozcan, S., & Sayek, S. (2009). FDI, productivity and financial development. World Economy, 32(1), 111-135.

Andrews, D., C. Criscuolo and P. Gal (2016), "The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy", *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris, https://doi.org/10.1787/63629cc9-en.

Arnold, J. M., & Javorcik, B. S. (2009). Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia. Journal of International Economics, 79(1), 42-53.

Athey, S., & Imbens, G. W. (2018). Design-based analysis in difference-in-differences settings with staggered adoption (No. w24963). National Bureau of Economic Research.

Bajgar, M., et al. (2020), "Coverage and representativeness of Orbis data", *OECD Science, Technology and Industry Working Papers*, No. 2020/06, OECD Publishing, Paris, https://doi.org/10.1787/c7bdaa03-en.

Balsvik, R., & Haller, S. A. (2010). Picking “lemons” or picking “cherries”? Domestic and foreign acquisitions in Norwegian manufacturing. *Scandinavian Journal of Economics*, *112*(2), 361-387.

Bandick, R. (2011). Foreign acquisition, wages and productivity. *The World Economy*, *34*(6), 931-951.

Bertrand, O., & Zitouna, H. (2008). Domestic versus cross-border acquisitions: which impact on the target firms’ performance? *Applied economics*, *40*(17), 2221-2238.

Bruno, R. L., & Cipollina, M. (2018). A meta-analysis of the indirect impact of foreign direct investment in old and new EU member states: Understanding productivity spillovers. *The World Economy*, *41*(5), 1342-1377.

Buckley, P. J., Elia, S., & Kafouros, M. (2014). Acquisitions by emerging market multinationals: Implications for firm performance. *Journal of World Business*, *49*(4), 611-632.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31-72.

Callaway, B., & Sant’Anna, P. H. (2020). Difference-in-differences with multiple time periods. Journal of Econometrics.

Carril-Caccia, F. (2020). Does the origin matter? The effects of cross-border mergers and acquisitions in France. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-10-2019-0823.

Chari, A., Chen, W., & Dominguez, K. M. (2012). Foreign ownership and firm performance: Emerging market acquisitions in the United States. *IMF Economic Review*, *60*(1), 1-42.

Cozza, C., Rabellotti, R., & Sanfilippo, M. (2015). The impact of outward FDI on the performance of Chinese firms. *China Economic Review*, *36*, 42-57.

Cui, L., & Jiang, F. (2012). State ownership effect on firms' FDI ownership decisions under institutional pressure: A study of Chinese outward-investing firms. *Journal of international business studies*, *43*(3), 264-284.

Cushman, D. O., & De Vita, G. (2017). Exchange rate regimes and FDI in developing countries: A propensity score matching approach. *Journal of International Money and Finance, 77*, 143-163.

Damioli, G., Gregori, W. D. (2021). Diplomatic relations and cross-border investments in the European Union. Publications Office of the European Union, Luxembourg, ISBN 978-92-76-32632-8, doi:10.2760/29780, JRC124250.

De Mello, L. R. (1999). Foreign direct investment-led growth: Evidence from time series and panel data. *Oxford Economic Papers 51 (1)*: 133–51. doi:10.1093/oep/51.1.133.

Djankov, S., & Hoekman, B. (2000). Foreign investment and productivity growth in Czech enterprises. *The World Bank Economic Review*, *14*(1), 49-64.

Dunning, J. H. (1998). Location and the multinational enterprise: a neglected factor? *Journal of international business studies*, *29*(1), 45-66.

Dunning, J. H. (2009). Location and the multinational enterprise: a neglected factor? *Journal of international business studies*, *40*(1), 5-19.

European Commission (2003). Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (Text with EEA relevance) (notified under document number C(2003) 1422), *OJ L 124, 20.5.2003, p. 36–41,* available at http://data.europa.eu/eli/reco/2003/361/oj

European Commission (2021). EU Competitiveness: Recent Trends, Drivers, and Links to Economic Policy, Publications Office of the European Union, Luxembourg. Doi:10.2760/856014.

Gal, P. (2013), "Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS", *OECD Economics Department Working Papers*, No. 1049, OECD Publishing, Paris, https://doi.org/10.1787/5k46dsb25ls6-en.

Girma, S., & Görg, H. (2002). Foreign ownership, returns to scale and productivity: Evidence from UK manufacturing establishments. *Returns to Scale and Productivity: Evidence from UK Manufacturing Establishments.* Centre for Economic Policy Research, Discussion Paper Series, No. 3503.

Girma, S., & Görg, H. (2007). Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. Journal of International Economics, 72(1), 97-112.

Girma, S., Kneller, R., & Pisu, M. (2007). Do exporters have anything to learn from foreign multinationals? *European Economic Review*, *51*(4), 993-1010.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., & Villegas-Sanchez, C. (2017). Capital allocation and productivity in South Europe. The Quarterly Journal of Economics, 132(4), 1915-1967.

Harris, R., & Robinson, C. (2002). The effect of foreign acquisitions on total factor productivity: plant-level evidence from UK manufacturing, 1987–1992. *Review of Economics and Statistics*, *84*(3), 562-568.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The review of economic studies, 64(4), 605-654.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. *American Economic Review*, *94*(3), 605-627.

Karolyi, G. Andrew, and Rose C. Liao. "State capitalism's global reach: Evidence from foreign acquisitions by state-owned companies." *Journal of Corporate Finance* 42 (2017): 367-391.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, *42*(3), 752-782.

Leuven, E. & Sianesi, B. (2003). PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. *EconPapers*. Software version 4.0.12 (30 January 2016).

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, *70*(2), 317-341.

Li, C., & Tanna, S. (2019). The impact of foreign direct investment on productivity: New evidence for developing countries. *Economic Modelling*, 80, 453-466.

Mattes, A. (2010). *International M&A: Evidence on effects of foreign takeovers* (No. 60). IAW Diskussionspapiere.

Mu, R., & Van de Walle, D. (2011). Rural roads and local market development in Vietnam. *The Journal of Development Studies*, *47*(5), 709-734.

McGuckin, R. H., & Nguyen, S. V. (1995). On productivity and plant ownership change: New evidence from the longitudinal research database. *The RAND Journal of Economics*, 257-276.

O'Donnell, C. J. (2011). The sources of productivity change in the manufacturing sectors of the US economy. Centre for efficiency and Productivity Analysis, University of Queensland, Working Paper Series, No. WP07/2011.

Pittiglio, R., & Reganati, F. (2019). Foreign direct investment productivity premium and foreign affiliates' heterogeneity: A comparison between advanced and emerging market overseas investments in the EU. *The World Economy*, *42*(10), 3030-3064.

Ramasamy, B., Yeung, M., & Laforet, S. (2012). China's outward foreign direct investment: Location choice and firm ownership. *Journal of world business*, *47*(1), 17-25.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Salis, S. (2008). Foreign acquisition and firm productivity: evidence from Slovenia. *World Economy*, *31*(8), 1030-1048.

Sanfilippo, M. (2015). FDI from emerging markets and the productivity gap—An analysis on affiliates of BRICS EMNEs in Europe. *International Business Review*, *24*(4), 665-676.

Schiffbauer, M., Siedschlag, I., & Ruane, F. (2017). Do foreign mergers and acquisitions boost firm productivity? *International Business Review*, *26*(6), 1124-1140.

Van Biesebroeck, J. (2008). The sensitivity of productivity estimates: Revisiting three important debates. *Journal of Business & Economic Statistics*, *26*(3), 311-328.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, *104*(3), 112-114.

Appendix 1

Table A1. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ln(Total Assets)	1.00						
(2) ln(Fixed Assets/Total Assets)	0.02	1.00					
(3) ln(Loans/Total Assets)	0.05	-0.03	1.00				
(4) ln(Op. costs/Turnover)	-0.05	0.00	0.08	1.00			
(5) ln(Profits/Total Assets)	-0.02	-0.10	-0.12	-0.52	1.00		
(6) Inflation	0.02	0.02	0.07	0.01	-0.02	1.00	
(7) ln(PerCapitaGDP)	0.21	-0.05	-0.01	0.00	0.06	0.22	1.00

Appendix 2

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 Rubins' 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. Propensity Score Matching, Logit regression output

	(1)
log(TFP)	0.583***
	(0.023)
Ln(No. Employees)	1.053***
	(0.056)
Ln(No. Employees)^2	-0.065***
	(0.005)
ln(Debts/Total Assets)	-0.442***
	(0.055)
ln(Op. costs/Total Assets)	0.540***
	(0.100)
ln(Profits/Total Assets)	-0.712***
	(0.081)
ln(Age)	0.409***
	(0.055)
ln(Age)^2	-0.115***
	(0.012)
Constant	-16.280***
	(0.457)
Observations	2,574,876
Pseudo R-squared	0.157
Log likelihood	-20,906.81
Country FE	Yes
Sector FE	Yes

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

Table A3. Balancing tests

	Mean		Bias (%)	Bias reduction (%)	t-test
	Treated	Control			p > t
log(TFP)	11.897	11.875	2.4	96.4	0.379
Ln(No. Employees)	4.615	4.630	-1.1	99.0	0.706
Ln(No. Employees)^2	23.790	23.582	1.5	98.3	0.610
ln(Op. costs/Total Assets)	0.744	0.758	-3.6	19.1	0.145
ln(Profits/Total Assets)	0.046	0.052	-4.0	2.2	0.186
ln(Debts/Total Assets)	0.181	0.176	3.1	-4.2	0.241
ln(Age)	2.587	2.618	-2.3	80.2	0.313
ln(Age)^2	8.171	8.307	-2.6	72.9	0.303

Notes: Matched sample tests.

Figure A1. Standardised % bias reductions

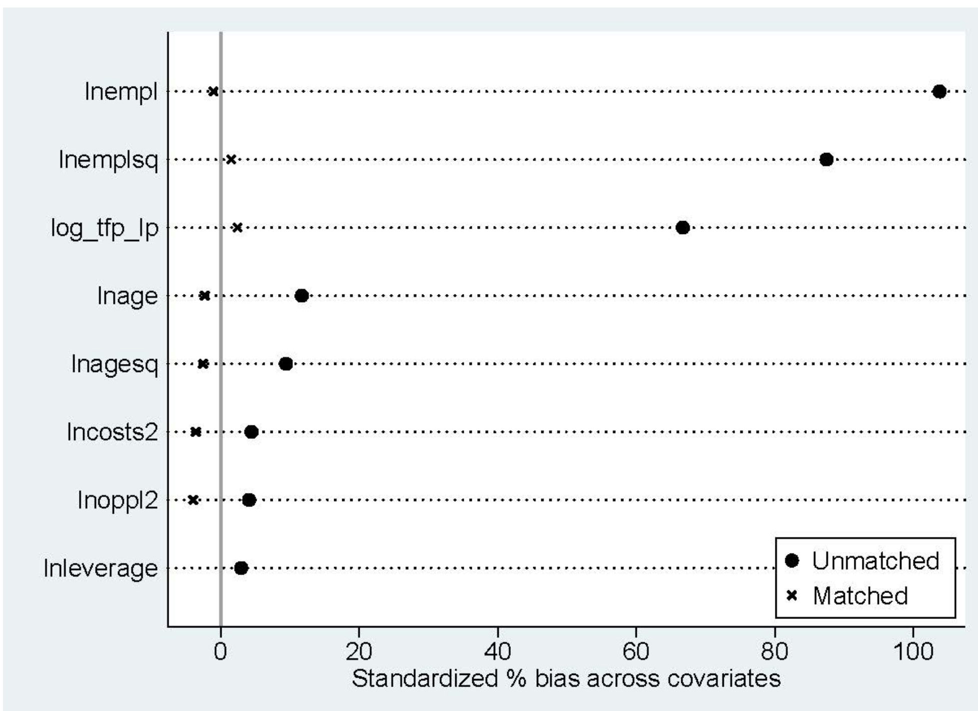


Table A4. Additional balancing statistics

	(1)	(2)		(3)	
	Pseudo-R^2	LR chi^2	p>chi^2	B	R
Unmatched	0.16	7997.56	0.00	169.20*	1.20
Matched	0.01	43.35	1.00	16.40	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[29]. 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:

[29] 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.

The European Commission's science and knowledge service
Joint Research Centre

JRC Mission
As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

EU Science, Research and Innovation

EU Science Hub

Publications Office of the European Union