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Abstract

In this paper, we test the contribution of foreign management on firms' competitiveness. We use a novel dataset on the careers of 165,084 managers employed by 13,106 companies in the United Kingdom in the period 2009-2017. We find that a domestic manufacturing firm becomes on average between 9% and 12% more productive after hiring at least one foreign manager. Interestingly, productivity gains by domestic firms after recruiting foreign managers are similar in magnitude to gains after foreign acquisitions as from previous literature. Eventually, we do not find significant gains by foreign-owned firms hiring foreign managers. Our identification strategy combines difference-in-difference and matching techniques to challenge reverse causality. We proxy firms' competitiveness either by total factor productivity or by technical efficiency derived from stochastic frontier analyses. Eventually, we argue that limits to the circulation of talents, as for example in case of a Brexit event, may hamper the allocation of labor productive resources.

JEL Classification: F22; F23; L23; L25; J61; M11

Keywords: managers; productivity; job mobility; spillovers; multinational enterprises; migration

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1 Introduction

Over the last decades, workers' mobility has increased dramatically. According to the Office for National Statistics (2019), the percentage of foreign employment in the United Kingdom has increased from 3.54% to 11.33% in the period 1997 to 2019. Certainly, the United Kingdom has been a very attractive destination in the last decades. Such a boost in immigration has been at the core of the referendum campaign for an exit from the European Union, i.e. a Brexit event, which could bring to new limits to the circulation of immigrant workers. Yet, according to ILO (2018), there are about 164 million migrant workers around the world. According to Baldwin (2016; 2019), future globalization will be shaped by an ever-increasing global mobility of workers who can also exploit new information technologies to combine work at a distance and a career across national borders. In this study, we examine how firms' competitiveness can be affected by the mobility of a peculiar category of workers, the managers, who are key contributors to the organization of a firm. As acknowledged by previous studies, managers' international mobility facilitates a transfer of knowledge among firms, as for example in the case of multinational enterprises, between a parent company and its subsidiaries (Cho, 2018). In particular, Mion and Opromolla (2014) and Mion et al. (2016) observe how knowledge diffusion through managers' mobility has an impact on a firm's export performance, relatively more when the knowledge transfer is market-specific. The importance of market-specific expertise on the internationalization of a firm is also studied by Meinen et al. (2018). In this contribution we take a step back if compared to previous literature, and we study whether foreign managers have an impact on firms' productivity, which in turn may lead (or not) to enhanced export performance. We argue that the nexus between management and productivity is a primary one[1] that is worth studying before looking at trade performance. Foreign managers may bring tacit knowledge that can be beneficial to a firm, whatever its strategy on domestic and foreign markets. The same holds in the case of foreign employees where it has been shown that they can act as a channel of knowledge transfer in high-tech industries (Santacreu-Vasut and Teshima, 2016). Previous literature identifies two main mechanisms through which foreign workers can have an impact: i) foreign experts can teach native workers at a lower cost than if they were self-learnt at home (Markusen and Trofimenko, 2009),

[1]Seminal works studied how managerial practices are a determinant of productivity differences across firms and countries (Bloom and Van Reenen, 2007; 2010; Bloom et al., 2013; Bloom et al., 2016).

or ii) the information set provided by high-skilled immigrants can be complementary to that of native employees (Laursen et al., 2019).

Eventually, we do find that the recruitment of at least one foreign manager for the first time has a positive and significant impact on firm-level productivity when a firm is domestic, whereas no significant impact is detected on the productivity of foreign-owned firms. In fact, the average productivity gains are in a range from 9% to 12% following recruitment. These gains are similar in magnitude to productivity gains detected after foreign acquisitions, as from previous literature (Bircan, 2019; Arnold and Javorcik, 2009). Hence, we argue that the possibility to recruit talents from abroad more generally allows to source from a wider pool of high skills that may not be present in the firm or on the domestic market. For our purpose, we take advantage of a novel dataset that matches the individual careers of 165,084 managers and the financial accounts of firms in the United Kingdom in the period 2009-2017. From our point of view, the United Kingdom is a policy-relevant case study since the country is bracing for the impact of a Brexit event, which will probably reduce the mobility of workers in the next future. Hence, we assess firms' competitiveness of UK firms by estimating TFP *à la* Ackerberg et al. (2015), and then we make our results robust to a measure of technical efficiency obtained by stochastic frontier analysis (Kumbhakar et al., 2014). Our identification strategy encompasses both difference-in-difference estimates on treated firms, i.e. firms that hired for the first time at least a foreign manager, as well as a propensity score matching method that first pairs treated firms with nearest untreated neighbors along different firm-level characteristics. In fact, our identification strategy borrows from the experience made on testing firm-level productivity premia after acquisitions of domestic firms by multinational enterprises (Bircan, 2019; Arnold and Javorcik, 2009).

The remainder of the paper is organized as follows. Section 2 describes the data and draws attention to preliminary evidence. Section 3 introduces results on the relationship between foreign management and firms' competitiveness. Section 4 concludes.

2 Data and preliminary evidence

We source data on careers of managers and firms' financial accounts in the United Kingdom from Orbis, a commercial database compiled by the Bureau Van Dijk[2], which is a consultancy firm controlled by Moody's Analytics. The database collects original information on management based on individual companies' filings, including their roles, dates of recruitment, nationality, gender, and age. Unfortunately, only scant information is included on managers' education and wages. For our purpose, we select managers working at least one year for manufacturing firms active in the United Kingdom in the period 2009-2017. Interestingly, the UK has a good coverage of management information if we compare with other countries. This is due to specific filing requirements asked to both private and public companies by the compilers of the UK national registry, the Companies House, following the Companies Act in 2006[3]. In this context, we consider a manager as any individual that participates to a company's board, committee or executive department. Therefore, we only exclude from our analysis advisors and shareholders as they do not participate to the daily administration of the company. We end up with a sample of 165,084 managers working for 13,106 manufacturing companies located in the United Kingdom. Please note, however, that any manager in our sample can cover more than one role in the same company, or she can participate to the management of more than one company at the same time. Since we have recruitment dates differentiated by both role and company for each individual manager, we can follow a manager's career within and across companies. In Appendix Table 10, we present some details on managers' levels of responsibility as included in our sample, where every individual covers at least one of those roles in a company at some point in our period of analysis. In following analyses, we consider the date of first hire as the earliest date a manager covered any role in that company. In the end, the nationality of managers is a crucial variable in our analysis. In our sample, we find that 16.42 % of managers have a foreign nationality. Table 1 presents the top 10 most common nationalities we detect in our sample. Please note how we adopt here a

[2]The Orbis database collects and standardizes firms' financial accounts from around the globe. Orbis data are increasingly used for firm-level studies on multinational enterprises, see for example Alviarez et al. (2017), Cravino and Levchenko (2017), Del Prete and Rungi (2017).

[3]In particular, the main legal concern is that individuals cannot be disqualified by the court from acting as company directors, and that they cannot be undischarged bankrupts. In a recent past, risk and compliance companies systematically scrutinized the ensemble of directors from the Companies House registry to unearth how many were included on international watchlists of individuals considered at high risk of crime. See, for example, The Times (2008)

conservative definition of a foreign manager, as for instance a manager that has a dual citizenship, including also UK, is still considered domestic. In this case, we want to exclude as much as possible from the set of foreign managers cases when an individual has never had any experience abroad, because for example she was raised in UK by foreign parents or because she has migrated relatively earlier in her age to UK. As largely expected, managers landing in UK companies come from around the globe. We find in our sample 27,117 foreign managers with 114 different foreign nationalities. The most represented country is the US, followed by Germany, Japan, and France. Overall, we find that 48.26% of foreign managers are citizens of the European Union and they represent about 7.93% of the total sample. Additionally, in Table 2, we show how many companies have foreign managers in the period 2009-2017, as well as the number of companies that hired for the first time at least one foreign manager in the same period, further separating between domestic and foreign-owned companies. As expected, it is more common for foreign companies to hire foreign managers, either because they interact more often with international markets or because they recruit managers from headquarters located abroad[4]. For sake of completeness, in Appendix Table 11, we also show the top 10 origin country of foreign-owned firms in our sample[5].

Table 1: Top 10 nationalities of foreign managers

Nationality	No. of managers
United States	7,557
Germany	3,160
Japan	2,751
France	2,383
Ireland	1,425
Netherlands	1,273
Italy	1,068
Sweden	996
South Africa	941
Denmark	782

Note: A foreign manager is a manager with a nationality different from UK. In case of multiple nationalities, including UK, the individual is considered a domestic manager.

[4]On the other hand, Ando et al., (2007) show that the experience of a foreign affiliate in a host country is negatively associated with the recruitment of parent-country nationals.

[5]The identification of foreign-owned companies follows international standards (OECD, 2005; UNCTAD, 2009; UNCTAD, 2016), according to which a subsidiary is controlled after a (direct or indirect) concentration of voting rights ($> 50\%$).

Table 2: Companies with foreign managers and new foreign hires in 2009-2017

	At least a foreign manager	At least a foreign new hire	Percentage
All firms	4,607	3,804	82.57 %
of which:			
Domestic firms	1,150	826	71.83%
Foreign subsidiaries	3,457	2,978	86.14%

Note: The table presents the number of firms with foreign managers (column 1), as well as the number of firms that recruited for the first time at least a foreign manager in 2009-2017 (columns 2), expressed also as a percentage (column 3).

2.1 Preliminary evidence on managers and productivity

Researchers across many fields have learnt a great deal about firm-level productivity since microdata on production activity have become available, and the evidence that management and productivity are correlated has been piling up over the decades (Syverson, 2011). Yet, as far as we know, there is still scant evidence that foreign management in particular plays a role in this correlation. For the purpose of our analyses, we exploit two different notions of productivity derived from recent literature. We take firm-level total factor productivity (TFP) as a baseline after we estimate it following the technique by Ackerberg et al. (2015), whose summary we report in an Appendix B. In this framework, TFP is traditionally interpreted as the portion of output growth not explained by growth in observed inputs. In addition, we estimate firm-level technical efficiency following stochastic frontier analyses (Kumbhakar et al., 2015). In Appendix C, we report a summary of the latter empirical approach, according to which any time a higher level of output is technically attainable for a given set of inputs, or any time the observed output can be produced using a smaller set of inputs, then a firm has a relatively inefficient production plan with respect to a frontier.

At this stage, we can already present some first correlations between the presence of foreign managers and the productivity of a firm. In the first two rows of Table 3, we present the results of least-squares binary regressions where the dependent variable is the (log of) TFP and, among regressors, a dummy identifies the presence of at least a foreign manager in the team without regard to her tenure in the firm. The binary regressions further include firms' characteristics (firm size, age, capital intensity, and wage

bill), industry and year fixed effects. The same exercise is repeated on separate subsets including domestic companies and subsidiaries of foreign firms, separately. Then, on a third row, we show the result of a similar binary regression performed on the entire sample, this time identifying with a dummy variable the subset of foreign-owned *vis à vis* domestic firms, besides regressors controlling for firm-level characteristics, industry and year fixed effects. Finally, we performe the exercise comparing the subset of foreign firms and the subset of domestic firms that employ at least one foreign manager. There are two points that are worth pointing out here. First, foreign-owned firms show a positive TFP premium if compared with domestic firms, and this finding is largely in line with past evidence (Helpman et al. 2004; Tomiura, 2007; Mayer et al. 2008; Arnold and Javorcik 2009; Bircan, 2009). The second point is a novelty of our study. We find that domestic companies that have any foreign managers in their team also have a TFP premium that is similar in size to the premium of foreign over domestic firms. Visual evidence reported in Figure 1 confirms the previous results. Similar findings are reported in an Appendix Table 12, where we performed t-tests on TFP distributions of companies that hired foreign managers in our period of analysis, and of those that did not. Indeed, at this stage, we can guess that recruiting talents from abroad allows domestic firms to increase competitiveness, because they may have access to a higher pool of managerial practices and market experiences, which can in turn benefit also native workers (Markusen and Trofimenko, 2009; Laursen et al., 2019). Interestingly, however, any following test that we perform shows that foreign subsidiaries do not show any TFP advantage from recruiting talents abroad. The ensemble of preliminary evidence in Table 3, Figure 1, and Appendix Table 12 motivates us to investigate further whether the recruitment of foreign managers has indeed a direct impact on productivity after challenging hypotheses of reverse causality. That is, we want to rule out that what we observe after simple correlations is just a phenomenon of cherry-picking, when more productive firms more likely hire talents from abroad.

Figure 1: TFP distributions

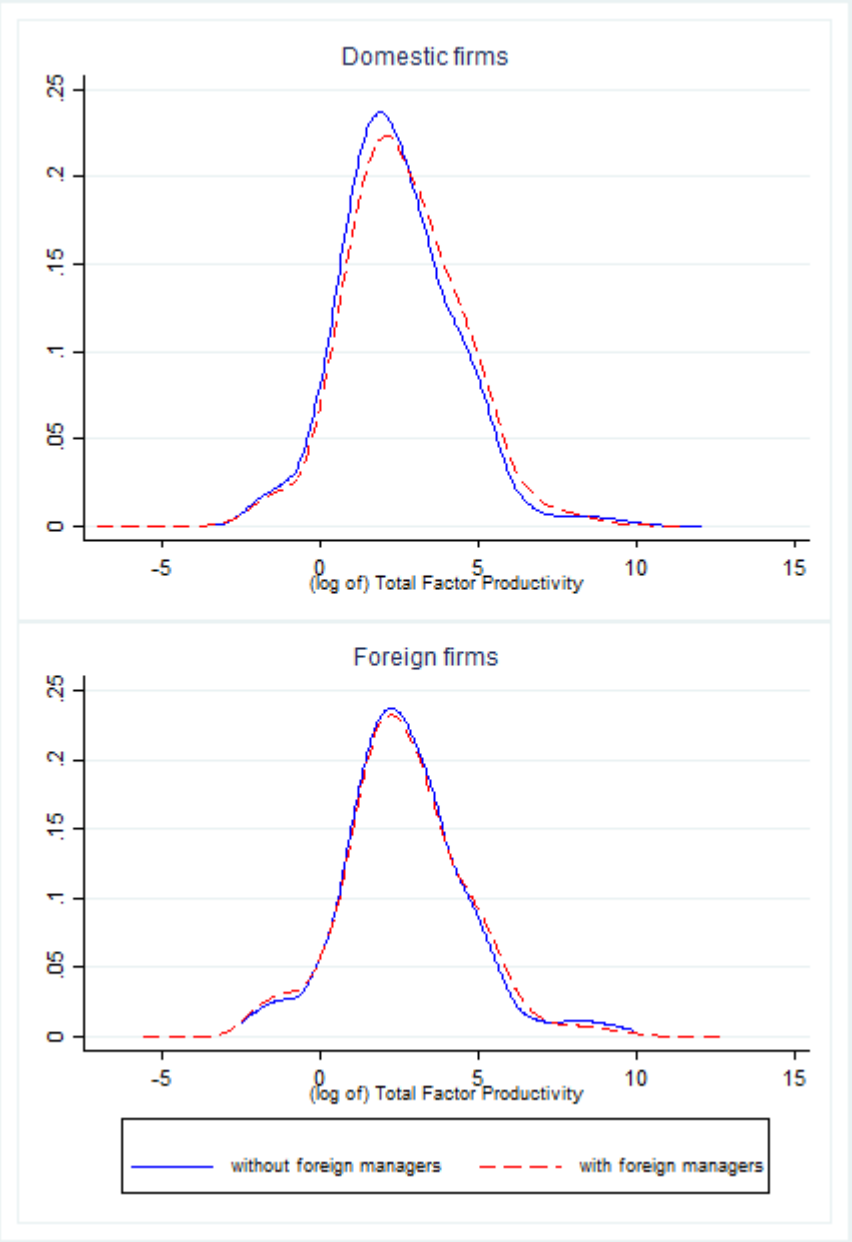


Table 3: TFP premia

	TFP premia	No. of firm *per* year obs
Domestic firms with vs. without foreign managers	0.045* (0.023)	31,874
Foreign subsidiaries with vs. without foreign managers	0.003 (0.019)	20,026
Foreign subsidiaries vs. domestic firms	0.054** (0.019)	51,900
Foreign subsidiaries vs. domestic firms with foreign managers	0.021 (0.022)	23,801

Note: TFP premia are estimated after OLS binary regressions where the dependent variable is log of TFP, including firm-level controls, industry and year fixed effects. Standard errors clustered by 2-digit industry in parenthesis. * and ** stand for $p < 0.1$ and $p < 0.05$, respectively.

3 Empirical strategy and Results

3.1 Baseline estimates

We assess the impact of hiring foreign managers on the productivity of a firm through a quasi-natural experiment. We start by identifying a group of firms that do not have any foreign managers at the beginning of the period. Hence, we consider a firm as treated if it recruited for the first time at least one foreign manager in a year of our period of analysis[6] in the period 2009-2017, whereas the control group includes firms that still do not have any foreign manager at the end of the period. To avoid cases of multiple treatments in a sequence, we drop from our sample the firm-per-year observations after a firm hires any foreign manager after the first event. For example, if a firm hired for the first time at least one foreign manager in 2010, and then it hired again a foreign manager in 2014, then we keep only the information related to the period from 2009 to 2013. Eventually, we end up with an unbalanced panel of 9,487 firms, of which 1,518 belong to the treatment group and 7,969 firms belong to the control group. At first, we estimate the following equation [7]:

[6]Please note how our treatment can include the recruitment of one or more foreign manager in a year. In principle, we could better identify a treated firm as a firm that hired the first foreign manager, since we have exact recruitment dates. However, this is not allowed by the firm-level outcome data, as TFPs are based on financial accounts collected on a yearly basis, when multiple recruitments can occur. In this case, we prefer keeping in the treated group also firms that hired more than once in a single year, to avoid a sample selection bias induced by the exclusion of most active firms on job markets.

[7]For a similar exercise performed to test firm-level productivity after foreign acquisitions, please see Bircan (2019).

$$y_{ijt} = \beta_0 + \beta_1 T_i \times Post_t + \beta' X_{it} + \gamma_j + \delta_t + \sum_k \eta_k \times \delta_t + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is the (log of) TFP of firm i in industry j and in year t, T_i is the treatment, i.e. the recruitment of at least one foreign manager and $Post_t$ is a binary variable equal to 1 if the period follows the recruitment. X_{it} includes firm-level characteristics like firm size, firm age, capital intensity, average wage bill, skill intensity, and foreign subsidiary status. γ_j and δ_t are 2-digit industry and year fixed effects, respectively. Since foreign managers may target specific plants based on some observed or unobserved characteristics, we may have an issue of self-selection. In this case, we include the term $\sum_k \eta_k \times \delta_t$ that represents a set of time trends controlling for the pre-recruitment age and size of the firm, as well as a set of industry fixed effects at the 4-digit level. In this term, we categorize firm age according to the number of years of life in the following way: [0,4], [5,9], [10,14], and 15+ years. On the other hand, we categorize firm size according to the number of employees in the following way: [0,9], [10,19], [20,49], [50,249], and 250+ employees. Results are reported in Table 4, where we consider only the subset of treated firms, hence β_1 measures TFP changes occurring within treated firms, after hiring at least one foreign manager. The same exercise is repeated for both domestic and foreign-owned firms, separately. In column 1 of Table 4, we find that there is a significant increase of 12.07% on TFP for domestic firms (log units 0.114; $e^{0.114} = 1.1207$) when they hire at least one foreign manager. The impact is slightly smaller (11.18%; log units 0.106; $e^{0.106} = 1.1118$) when we control for industry-per-year fixed effects in column 2 of the same table. There are many skills that a talent from abroad can provide to a domestic firm to boost productivity. More in general, we can argue that a newly-hired high-skilled immigrant can teach to native workers what the latter could otherwise find difficult to learn by themselves (Markusen and Trofimenko, 2009), or she can bring skills that are just complementary to the ones that are already present in the team of the recruiting firm (Laursen et al., 2019). Apparently, there is no significant change in the productivity of foreign-owned subsidiaries after they hire at least one foreign manager. In this case, it is possible that the most productivity spillovers already occurred at the moment of an acquisition by a multinational enterprise (Bircan, 2019; Arnold and Javorcik, 2009).

Table 4: Foreign managers and TFP - baseline estimates

	(1)	(2)
Dep. variable:	(log) TFP	(log) TFP
Panel A: All firms		
Hired × Post-recruitment	0.013	0.015
	(0.020)	(0.021)
R^2	0.940	0.942
No. of obs.	3,957	3,957
Panel B: Domestic firms		
Hired × Post-recruitment	0.114***	0.106**
	(0.038)	(0.040)
R^2	0.922	0.926
No. of obs.	1,670	1,670
Panel C: Foreign subsidiaries		
Hired × Post-recruitment	-0.042	-0.044
	(0.026)	(0.028)
R^2	0.961	0.964
No. of obs.	2,287	2,287
Panels A, B and C:		
Firm controls	Yes	Yes
4-digit Industry, age, size trends	Yes	Yes
Industry effects	Yes	
Year effects	Yes	
Industry × Year effects		Yes

Note: The table reports estimates of Eq. (1) on treated firms only, i.e. firms that hired at least one foreign manager for the first time in the period of analysis. Coefficients are in log units. Standard errors in parentheses are clustered at the 2-digit industry. Firm-level controls include age, employment, capital intensity, average wages, skill intensity and, for Panel A, foreign subsidiary status. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.2 Propensity-score matching and Diff-in-Diff

Even though, in the previous exercise, we control for pre-recruitment industry trends and several covariates, part of the effect on productivity after the recruitment can still

be due to the specific ability of a firm to target foreign talents. Therefore, in this Section, we perform an exercise that further challenges the direction of causality. We apply a matching procedure to pair firms included in the treatment group with their peers in the control group that share similar characteristics. In particular, we implement a one-to-one nearest neighbour matching method performed within the same 2-digit industry and year cell. All time-variant explanatory variables are lagged one year to reflect the pre-treatment period. The explanatory variables are chosen following previous literature that studied the impact of foreign acquisitions (Arnold and Javorcik, 2009; Bircan, 2019), since we can assume that the recruitment of foreign managers is endogenous to a similar set of observable firms' characteristics: technological progress, firm age, firm size, the average composition of employment, capital intensity, skill intensity, and ownership status. Table 5 presents the result of the probit model.

Table 5: Probit estimates - Predicting the recruitment of foreign managers

Dep variable: Hire=1 or 0			
TFP_{t-1}	0.131	Age^2_{t-1}	-0.013
	(0.113)		(0.013)
$TFP_{t-1}\times$ Age_{t-1}	-0.014	$\text{Capital intensity}_{t-1}$	0.305**
	(0.012)		(0.125)
Employment_{t-1}	-0.176	$\text{Capital intensity}_{t-1} \times \text{Age}_{t-1}$	-0.031**
	(0.143)		(0.014)
$\text{Employment}_{t-1}\times$ Age_{t-1}	0.042***	$\text{Skill intensity}_{t-1}$	1.051***
	(0.016)		(0.190)
$\text{Average wages}_{t-1}$	0.109**	$\text{Skill intensity}^2_{t-1}$	-0.202***
	(0.048)		(0.060)
Age_{t-1}	0.187	Foreign subsidiary	1.220***
	(0.231)		(0.042)
Pseudo R^2	0.194		
No. of obs.	26,783		

Note: All variables are in logs except capital intensity, skill intensity and foreign subsidiary status. Standard errors clustered by 2-digit industry in parentheses. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

The results indicate that a capital-intensive firm with a higher wage bill more likely hires a foreign manager. Moreover, in line with descriptive statistics, foreign managers

preferably work for foreign-owned companies. On the other hand, skill intensity has an inverted U-shape. Hence, the odds of hiring a foreign manager increase when this ratio is growing but up to a point, when it starts dropping. The age of the firm has a significant correlation with new hires of foreign managers only when we control for its interaction with employment as a proxy for firm size, and for capital intensity. Finally, to assess how well the propensity score matching performs in our case, we implement a balancing test. That is, we compare the averages of all the time-variant covariates assigned to the matching procedure. Table 6 shows the averages of the treatment and the control group, respectively, for all 505 matched pairs of companies. Eventually, we find that there is no *ex-post* statistically significant difference along the set of variables that we included for the matching. Having ensured that there is a good match among pairs, we proceed to diff-in-diff estimates of Eq. (1) that we report in Table 7. It is immediately evident how coefficients are similar to those of Table 4, where we considered only the subset of treated firms. Once again, when we focus on the case of domestic companies (Panel B), we find that TFP arises after hiring foreign managers for the first time. In this case, the TFP growth rate is 10.30% (log units 0.098, $e^{0.098} = 1.1030$) and 9.97% (log units 0.095; $e^{0.095} = 1.0997$), respectively. In line with both descriptive statistics and previous estimates, foreign subsidiaries do not benefit from any significant increase in TFP after hiring foreign managers. In fact, we argue, it is possible that main TFP gains already occurred at the moment the firm was acquired from foreign headquarters, i.e. after a firm first got in touch with a large pool of international experiences.

Table 6: Balancing test on the nearest-neighbour matching procedure

	Average treated	Average control	t-test	p-value
TFP_{t-1}	2.588	2.525	0.62	0.537
Employment_{t-1}	4.615	4.694	-1.06	0.292
$\text{Average wages}_{t-1}$	5.835	5.804	1.13	0.260
Age_{t-1}	8.875	8.948	-1.17	0.241
$\text{Capital intensity}_{t-1}$	5.300	5.259	0.50	0.619
$\text{Skill intensity}_{t-1}$	0.082	0.070	1.07	0.287

Note: The table reports averages and t-tests for variables used in previous probit estimates after constructing the nearest-neighbour control group.

Table 7: Foreign managers and TFP - DID on the matched sample

	(1)	(2)
Dep. variable:	(log) TFP	(log) TFP
Panel A: All firms		
Hired × Post-recruitment	0.036	0.038
	(0.023)	(0.024)
R^2	0.942	0.944
No. of obs.	6,183	6,183
Panel B: Domestic firms		
Hired × Post-recruitment	0.098***	0.095***
	(0.029)	(0.028)
R^2	0.927	0.930
No. of obs.	2,962	2,962
Panel C: Foreign subsidiaries		
Hired × Post-recruitment	-0.018	-0.016
	(0.033)	(0.034)
R^2	0.961	0.963
No. of obs.	3,221	3,221
Panels A, B and C:		
Firm controls	Yes	Yes
4-digit Industry, age, size trends	Yes	Yes
Industry effects	Yes	
Year effects	Yes	
Industry × Year effects		Yes

Note: The table reports estimates of Eq. (1) for the matched sample. Standard errors clustered at the 2-digit industry level in parentheses. Coefficients in log units. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity and, for Panel A, foreign subsidiary status. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.3 Robustness check: technical efficiency

In this section, we validate our results by performing the same empirical exercises using technical efficiency from stochastic frontier analyses as an alternative proxy for firms' competitiveness. Following this framework, we define a production plan as technically

inefficient when a higher level of output is attainable for a given set of inputs, or when the observed output can be produced using a smaller set of inputs (Kumbhakar et al., 2015). This is a different perspective, where the managerial decision-making process has been already considered as a crucial determinant of technical efficiency (see for example Wilson et al., 2001). In Appendix C, we provide details on the estimation of firm-level technical efficiencies, which could be further disaggregated into a time-invariant and a time-variant component. In Appendix Figure 2, we also report the evolution over time of both components. In our case, we consider the overall technical efficiency (OTE) as the measure of firm-level competitiveness[8]. By construction, the value of OTE ranges between zero and one, and it indicates how close the firm is to the production frontier. In this context, we test the hypothesis that foreign managers increase the ability of a firm to achieve a production level closer to its empirical frontier. Following the same steps of previous paragraphs, we first estimate the change before and after the treatment for the sample of treated firms only. Thereafter, we perform a diff-in-diff analysis on a matched sample, controlling for the same firm-level characteristics included in Table 5. Table 8 presents the results for the treated firms only, where patterns are similar but weakly or not at all significant. Specifically, when we consider the case of domestic companies, we still find a weakly positive coefficient in the first column. Statistical significance is lost when we include industry-per-year fixed effects, hence challenging the firm-level outcome variation to check for idiosyncratic market shocks. Since we cannot exclude that the recruitment of foreign managers is still endogenous to a set of observable firms' characteristics, we apply once again the matching technique described in the previous section. Result reported in (Table 9) show that domestic firms increase their technical efficiency by 0.5% after the recruitment of foreign management. Similarly to previous estimates, we cannot say that foreign subsidiaries benefit from the recruitment of foreign management.

[8]OTE is the product of persistent (time-invariant) and residual (time-variant) technical efficiency. See also Manevska-Tasevska et al. (2017), who show that different management practices may affect each component of technical efficiency in a different way. However, in our case we do not find a significant difference in trends over time.

Table 8: Foreign managers and technical efficiency - Baseline estimates

	(1)	(2)
Dep. variable:	OTE	OTE
Panel A: All firms		
Hired × Post-recruitment	0.001	0.001
	(0.002)	(0.002)
R^2	0.080	0.151
No. of obs.	3,955	3,955
Panel B: Domestic firms		
Hired × Post-recruitment	0.008*	0.008
	(0.004)	(0.005)
R^2	0.114	0.236
No. of obs.	1,670	1,670
Panel C: Foreign subsidiaries		
Hired × Post-recruitment	-0.005*	-0.005
	(0.002)	(0.003)
R^2	0.093	0.223
No. of obs.	2,285	2,285
Panels A, B and C:		
Firm controls	Yes	Yes
4-digit Industry, age, size trends	Yes	Yes
Industry effects	Yes	
Year effects	Yes	
Industry × Year effects		Yes

Note: The table reports estimates of Eq. (1) on treated firms only. Standard errors clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity and, for Panel A, foreign subsidiary status. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

Table 9: Foreign managers and technical efficiency - DID on the matched sample

	(1)	(2)
Dep. variable:	OTE	OTE
Panel A: All firms		
Hired × Post-recruitment	0.001	0.001
	(0.001)	(0.001)
R^2	0.082	0.144
No. of obs.	6,181	6,181
Panel B: Domestic firms		
Hired × Post-recruitment	0.005**	0.005**
	(0.002)	(0.002)
R^2	0.096	0.176
No. of obs.	2,962	2,962
Panel C: Foreign subsidiaries		
Hired × Post-recruitment	-0.003	-0.003
	(0.003)	(0.003)
R^2	0.099	0.179
No. of obs.	3,219	3,219
Panels A, B and C:		
Firm controls	Yes	Yes
4-digit Industry, age, size trends	Yes	Yes
Industry effects	Yes	
Year effects	Yes	
Industry × Year effects		Yes

Note: The table reports estimation results of Eq. (1). The sample consists of firms that hired at least one foreign manager and their matched controls. Standard errors are clustered at the 2-digit industry level and given in parentheses. Firm-level controls include age, employment, capital intensity, average wages, skill intensity and, for Panel A, foreign subsidiary status. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

4 Conclusion

As far as we know, no previous work has addressed the primary relationship between foreign management and firm-level productivity. In the case of the United Kingdom,

we find that domestic manufacturing firms largely benefit from hiring foreign managers. We find that their productivity increase in a range between 9% and 12% after recruiting. In fact, recruiting talents from abroad can allow firms to have access to a wider pool of skills than the ones available on the domestic market. After recruitment, foreign managers can share better managerial practices and different market experiences, or their skills can just be complementary to the ones by the native workers. Interestingly, we detect no significant gains by foreign-owned firms hiring for the first time foreign managers. In this case, we argue that productivity spillovers could already have occurred after the acquisition by foreign headquarters, when local subsidiaries become part of a multinational enterprise. More in general, our findings suggest that the recruitment of managerial talents from abroad can be a valid alternative to exploit international technological spillovers. In this perspective, we can argue that the introduction of barriers to the circulation of talents, as for example after a Brexit event, could hamper the competitiveness of domestic manufacturing industries.

Appendix A: Additional Tables and Graphs

Table 10: Board, committee or department in which managers' belong

Title	No. of managers
Senior management	113,906
Board of Directors	99,163
Operations & Production & Manufacturing	11,322
Sales & Retail	8,923
Finance & Accounting	6,458
Administration department	4,885
Human Resources (HR)	4,008
Information Technology (IT) & Information Systems (IS)	3,367
Purchasing & Procurement	3,261
Research & Development / Engineering	3,091
Marketing & Advertising	2,816
Health & Safety	680
Branch Office	271
Legal/Compliance department	128
Product/Project/Market Management	126
Executive Committee	119
Audit Committee	61
Nomination Committee	58
Remuneration/Compensation Committee	53
Corporate Governance Committee	35
Supervisory Board	17
Risk Committee	11
Safety Committee	7
Executive Board	5
Environment Committee	4
Public & Government Affairs	4
Quality Assurance	4
Ethics Committee	3
Others & Unspecified	18,811

Note: The table reports roles of managers as present from our sample. Any manager can cover more than one role in the same company, or she can participate to the management of more than one company at the same time. We exclude from original sources only shareholders and advisors without any role in the daily management of the firm. Please note how names of roles are not standard across firms, as they may follow the specific responsibilities attributed to individuals autonomously within firms.

Table 11: Top 10 origin countries of foreign-owned firms

Nationality	No. of companies
United States	1,321
Germany	394
Japan	279
France	262
Sweden	183
Switzerland	157
Ireland	155
Netherlands	146
Italy	105
Luxembourg	96

Note: We define a foreign-owned firm following international standards ((OECD, 2005; UNCTAD, 2009; UNCTAD, 2016), according to which a subsidiary is controlled after a (direct or indirect) concentration of voting rights ($> 50\%$).

Table 12: T-tests on TFP distributions for firms with and without foreign managers

Average value of TFP	With foreign managers	Without foreign managers	With new foreign managers	Without new foreign managers	Total
All firms	2.638***	2.468***	2.658***	2.516***	2.528
	(0.013)	(0.009)	(0.028)	(0.008)	(0.008)
Domestic firms	2.656***	2.432***	2.607**	2.455**	2.458
	(0.027)	(0.010)	(0.068)	(0.009)	(0.009)
Foreign subsidiaries	2.634	2.670	2.667	2.637	2.643
	(0.015)	(0.025)	(0.031)	(0.014)	(0.013)

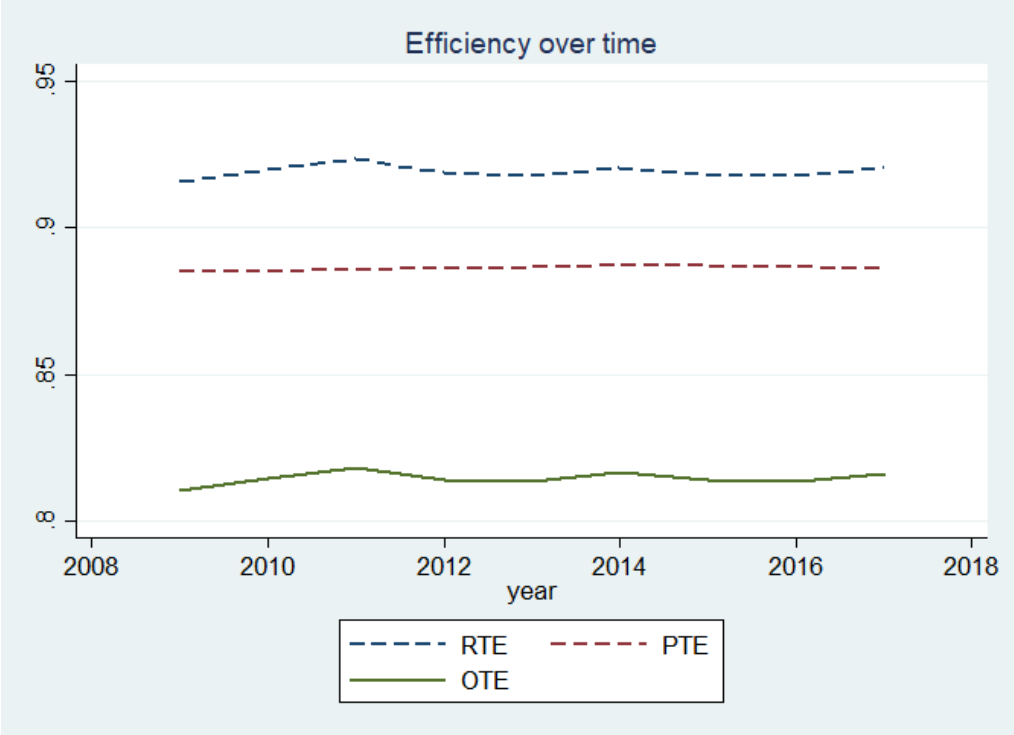
Note: Columns (2) and (3) show the TFP averages of firms with and without foreign managers, respectively. Columns (4) and (5) show the TFP averages of firms with and without new foreign recruits in 2009-2017. The last column pools all firms together. Standard deviations in parenthesis. We test the null hypotheses that averages are equal after a t-test. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

Table 13: OTE premia

	OTE premia	No. of firm *per* year obs
Domestic firms with vs. without foreign managers	0.001* (0.001)	31,830
Foreign subsidiaries with vs. without foreign managers	-0.001 (0.001)	20,015
Foreign subsidiaries vs. domestic firms	0.001 (0.001)	51,845
Foreign subsidiaries vs. domestic firms with foreign managers	-0.001 (0.001)	23,788

Note: OTE premia are estimated after OLS binary regressions, where the dependent variable is OTE, including firm-level controls, industry and year fixed effects. Standard errors clustered by 2-digit industry in parentheses. * and ** stand for $p < 0.1$ and $p < 0.05$.

Figure 2: Firm-level components of technical efficiency in the period 2009-2017



Note: The figure shows the evolution of the average level of each component of firm-level technical efficiency over time: Residual Technical Efficiency (RTE), Persistent Technical Efficiency (PTE) and Overall Technical Efficiency (OTE) as they are estimated by the model of Kumbhakar et al., (2014).

Appendix B: Total Factor Productivity *à la* Ackerberg, Caves and Frazer (2015)

The major identification problem in estimating a firm-level production function is that input choices can depend on shocks unobserved by the econometrician at the end of the period, when firms' financial accounts typically become available. Therefore, an endogeneity problem can arise such that the observed combination of production factors is simultaneous to the possibly unobserved shocks, hence OLS estimates are inconsistent. In this context, the model of Ackerberg et al. (2015) follows on previous efforts by Olley & Pakes (1996), Levinsohn & Perin (2003), and Woolridge (2009). Here, we briefly summarize the empirical framework. Let us start considering the following production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

where y_{it} is the log of output (or value added), k_{it} is the log of capital stock, l_{it} is the log of labour input, ω_{it} is the unobserved productivity component and ε_{it} is the error term of firm i at time t. The model imposes the following assumptions:

- **Assumption 1**: The firm's information set I_{it} includes current and past productivity shocks $\{\omega_{i\tau}\}_{\tau=0}^{t}$ but does not include future productivity shocks $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. The transitory shocks ε_{it} satisfy $E[\varepsilon_{it}|I_{it}] = 0$.

- **Assumption 2**: Productivity shocks evolve according to a First Order Markov Distribution

  $$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it})$$

  with a distribution that is known to firms and stochastically increasing in ω_{it}.

- **Assumption 3**: Firms accumulate capital according to

  $$k_{it} = \kappa(k_{it-1}, i_{it-1})$$

  where investment i_{it-1} is chosen at $t-1$. Labour input may potentially be dynamic and is chosen at period t, $t-1$ or $t-b$ $(0 < b < 1)$.

- **Assumption 4**: The intermediate input demand for a firm is given by

  $$m_{it} = f(k_{it}, l_{it}, \omega_{it}) \tag{3}$$

- **Assumption 5**: $f(k_{it}, l_{it}, \omega_{it})$ is strictly increasing in ω_{it}.

Given the above assumptions, from Eq. (3) we have $\omega_{it} = f^{-1}(k_{it}, l_{it}, m_{it})$. Substituting in the production function, we have

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f^{-1}(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} = \Phi_t(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \tag{4}$$

which leads to the following first stage moment condition:

$$E[\varepsilon_{it}|I_{it}] = y_{it} - \Phi_t(k_{it}, l_{it}, m_{it}) = 0 \tag{5}$$

Assumptions 1 and 2 imply that we can decompose ω_{it} into its conditional expectation at time $t-1$, and an innovation term, that is,

$$\omega_{it} = E[\omega_{it}|I_{it-1}] + \xi_{it} = E[\omega_{it}|\omega_{t-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$$

where $E[\xi_{it}|I_{it-1}] = 0$.

So we obtain the estimated values $\hat{\Phi}_t(k_{it}, l_{it}, m_{it})$ using the following second stage conditional moment:

$$\begin{aligned} & E[\xi_{it} + \varepsilon_{it}|I_{it-1}] \\ = E[y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - g(\Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) - \beta_0 - \beta_k k_{it-1} - \beta_l l_{it-1})|I_{it-1}] \\ & = 0 \end{aligned} \tag{6}$$

Now, consider a model where $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$. Suppose that the first stage is performed by an OLS regression of y_{it} on a high-order polynomial in (k_{it}, l_{it}, m_{it}) to obtain $\hat{\Phi}_t(k_{it}, l_{it}, m_{it})$. If labour is assumed to be chosen after time $t-1$, then a natural set of four second stage moment conditions to estimate $\beta_0, \beta_k, \beta_l$ and ρ is

$$\begin{aligned} E\Big[& y_{it} - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - \rho \cdot (\Phi_{t-1}(k_{t-1}, l_{t-1}, m_{t-1}) - \beta_0 - \beta_k k_{it-1} - \beta_l l_{it-1})) \\ & \otimes \begin{pmatrix} 1 \\ k_{it} \\ l_{it-1} \\ \Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) \end{pmatrix} \Big] = 0 \end{aligned} \tag{7}$$

Appendix C: Technical efficiency *à la* Kumbhakar, Lien and Hardaker (2014)

Kumbhakar et al. (2014) introduce one of the most recent models for estimating technical efficiency applying stochastic frontier analysis. Thanks to this approach, it is possible to split the error term of a firm-level production function into four components in order to consider different factors affecting output[9]: i) time-invariant firms' heterogeneity; ii) short-run time-varying (or residual) inefficiency; iii) persistent or time-invariant inefficiency; iv) random shocks. Hence, the setup of the model is the following:

$$y_{it} = \alpha_o + f(x_{it};\beta) + \mu_i + v_{it} - \eta_i - u_{it} \tag{8}$$

where y_{it} is the output of firm i at time t, $f(x_{it};\beta)$ is a translog production function, μ_i are firm effects, v_{it} is the noise and finally, $\eta_i > 0$ and $u_{it} > 0$ are the time-invariant and time-variant inefficiency components respectively. This model is one of the most innovative in the literature of stochastic frontier analysis. The main reason is the fact that it is able to capture firm effects, time invariant inefficiency and time-varying inefficiency all in the same model, in contrast with previous ones that were able to capture one or two of these components only.

The estimation of Eq. (8) has been applied in a 3-step procedure. At first, we rewrite the model in the following way:

$$y_{it} = \alpha_0^* + f(x_{it};\beta) + \alpha_i + \varepsilon_{it} \tag{9}$$

where

$$\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it}) \tag{10}$$

$$\alpha_i = \mu_i - \eta_i + E(u_{it}) \tag{11}$$

$$\varepsilon_{it} = v_{it} - u_{it} + E(u_{it}) \tag{12}$$

The first step is to estimate $\hat{\beta}$ by using random-effects panel regression to obtain estimates of α_i and ε_{it}, namely $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$. The second step is to estimate the time-varying inefficiency component u_{it}. To do so, we use the predicted value $\hat{\varepsilon}_{it}$ obtained

[9]See also Kumbhakar et al. (2015) for a detailed review of stochastic frontier models for estimating technical efficiency.

in the first step. Under the assumption that v_{it} is i.i.d. $N(0, \sigma_v^2)$ and u_{it} is $N^+(0, \sigma_u^2)$, we estimate u_{it} from Eq. (12). The third step is to estimate η_i from Eq. (11). Under the assumption that μ_i is i.i.d. $N(0, \sigma_\mu^2)$, η_i is i.i.d. $N^+(0, \sigma_\eta^2)$ we obtain estimates for the persistent technical inefficiency components η_i.

Finally, the residual and persistent technical efficiency are estimated respectively from the following equations:

$$\text{RTE} = \exp(-u_{it}|\varepsilon_{it})$$

$$\text{PTE} = \exp(-\eta_i)$$

The overal technical efficiency is obtained by

$$\text{OTE} = \text{PTE} \times \text{RTE} \tag{13}$$

Finally, we are able to depict the mean values of RTE, PTE and OTE over time. See Appendix Figure 2.

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