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Catching-up to foreign technology? Evidence on the "Veblen–Gerschenkron" effect of foreign investments

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Abstract

The presence of foreign multinational enterprises may benefit local economies. In particular, highly productive foreign-owned firms may promote the technological catch-up of local firms. This channel of spillovers is defined as the "Veblen–Gerschenkron" effect of foreign direct investment and is analyzed in this article. Rather than the overall concentration of foreign-owned plants in a region or sector, it is their productivity advantage that determines the positive effect on domestic firms in geographical and technological proximity. We test this hypothesis using new firm-level data for German and Italian manufacturing firms during the 1990s. These two countries are particularly interesting due to the low productivity of domestic firms in some regions of East Germany and the Mezzogiorno. We find evidence of a significant (statistically and economically) Veblen–Gerschenkron effect which is robust to various ways of measuring the total factor productivity (TFP) of firms and to different empirical specifications.

JEL classification: F23; O47; R11
Keywords: Veblen–Gerschenkron effect; FDI; Technological catch-up; Local spillovers

1. Introduction

Does foreign direct investment (FDI) benefit the domestic firms of the host country? And if so, through which channels are these benefits received? These long standing and important

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questions have attracted much interest among economists. Strictly from a theoretical perspective, the answer remains unclear: FDI can either help or harm domestic firms, depending on the intensity levels of various effects. Ultimately the net effects of FDI have to be evaluated empirically, but recent empirical studies have found both positive to negative effects, depending on the focus, the data and the method used.[1] This article contributes another piece of evidence to this issue by focusing on a potentially important (but largely neglected) determinant of spillovers from FDI to domestic firms,[2] namely the productive advantage foreign firms have over domestic firms within a sector and region.

According to Blomström et al. (2001), "foreign investors make available (directly or indirectly) appropriable technology to host country businesses. Appropriable technology should be viewed broadly as any tangible or intangible resource that can generate economic rent for host country firms, ... by improving total factor productivity." By this we should believe that technological spillovers will depend both on the technological edge foreign firms have over domestic firms, and on the geographical proximity of foreign firms to domestic firms. Hence, our variable of interest will be the productivity of foreign-owned firms, and in particular the difference in productivity between foreign and domestic firms in a sector-region. Since the work of Caves (1974), economists have honed their attention on the concentration of foreign-owned firms (measured as the share of FDI capital or share of FDI workers) within a sector and/or a region as the source (and proxy) of potential spillovers.[3] In an influential paper, however, Aitken and Harrison (1999) have shown that properly controlling for unobserved region-specific effects eliminates most of the effect of FDI density on domestic firms' productivity. This may occur because certain local characteristics that attract FDI[4] (such as the presence of a high-quality labor force, large local markets, good infrastructures and good administration) also enhance the productivity of domestic firms, generating a spurious correlation between these two variables. Once these factors are properly controlled for, no correlation survives.

This result, however, does not necessarily imply that there are no spillovers from FDI. The density of FDI may simply not be the right source of (and proxy for) spillovers. Rather the productivity advantage enjoyed by foreign firms may potentially be a more important source of spillovers. While the largest concentration of foreign firms normally occurs in regions and sectors where domestic firms are already highly productive, the largest effect of foreign firms on domestic ones could be in backward regions, where FDI concentration is small but their productivity effects are large due to the scope for technological catch-up. The effects of this mechanism are labeled the "Veblen–Gerschenkron" effect (or VG effect for brevity) in acknowledgement of the early intuitions of Veblen (1915) and Gerschenkron (1952).

[1] Advocates of a positive role of FDI through technological transfer are Findlay (1978), Das (1987), and Wang and Blomström (1992). Rodriguez-Clare (1993) and Markusen and Venables (1999) argue that they benefit local suppliers and local consumers. Fosfuri et al. (2001) and Glass and Saggi (1998, 2002) document that they could increase the human capital of the local labor force. On the other hand, FDI could out-compete local firms forcing them out of production without employing local labor because of skill mismatch. This is argued in Aitken and Harrison (1999). A combination is Barrios et al. (2005).

[2] For a survey of the literature, see Blomström and Kokko (1998). An interesting meta-analysis of the different research results is Görg and Strobl (2001).

[3] There have been some studies aimed at quantifying some important channels of knowledge diffusion via FDI. Branstetter (2001) uses patent citation data while Cassiman and Veugelers (2002) rely on survey data. These studies, however, address specific channels of spillovers rather than their overall impact on productivity.

[4] See, for example, Shannon and Zeile (1999) for the US and Stirböck (2001) for Europe.

The original formulation of the VG effect, originally proposed by Findlay (1978), states that technologically disadvantaged regions are more likely to benefit from spillovers from FDI, and may as a consequence experience stronger productivity growth relative to more advanced regions. Using a new data set of domestic and foreign-owned manufacturing firms in Italy and Germany for the period 1993–1999, we test the hypothesis that the productivity edge of foreign-owned firms in a sector and region is an important determinant of productivity growth for domestic firms in the same sector and region. The positive effect of the productivity of foreign-owned firms on the subsequent growth of domestic firms in a sector and region will be referred to as the Veblen–Gerschenkron (VG) effect. On one hand, some recent studies (Haddad and Harrison, 1993; Kokko, 1994; Sjöholm, 1999; Castellani and Zanfei, 2003) have emphasized the beneficial effects of FDI on domestic firms due to intra-industry technology spillovers and subsequent technological catch-up. On the other hand, studies on the diffusion of technological knowledge based on patent and innovation data (Jaffe et al., 1993; Audretsch and Feldman, 1996; Peri, 2005) have emphasized the high degree of localization that characterizes these flows. Our analysis combines this regional dimension of FDI spillovers with the importance of the productivity-advantage of foreign-owned firms in generating them. Such a method allows us to identify the VG effect while controlling for sector-specific and firm-specific determinants of productivity and growth.

A second novel contribution of our study is the computation and use of as many as five measures of total factor productivity at the firm level, each based on different methods and different assumptions. Because measures of total factor productivity are always indirect (they are based on the calculation of a “residual” from a production function) they can become polluted by systematically unobserved errors. Our measures of firm-level TFP address three important problems, namely the endogeneity of foreign ownership, unobserved heterogeneity of firms and selection of the sample. Each measurement method addresses one problem at the exclusion of the other problems. However, using each of these TFP measures, we find significant and similar estimates of the VG effect. This substantially reduces our concerns for spurious results.

The final novel element here is that our paper focuses on the interesting cases of Italy and reunified Germany. Our new data set contains geographic identifiers that allow us to locate firms within 1 of 103 Italian Provinces or 16 German Regions (Bundesländer). Italy and Germany have well-known issues of uneven regional development, and the cross-sectional variations in productivity across firms are quite large. Our study exploits these differences and provides some evidence on the role of foreign investments in promoting productivity growth in less-developed regions. In particular, Germany provides a very interesting case study, since the unification and subsequent inflow of firms from Western Europe put eastern firms in touch with new technologies after 50 years of almost complete isolation. East German firms had exhibited substantial technological backwardness upon the sudden inflow of western firms, generating the ideal conditions for strong VG effects.

Our estimates show the presence of positive and significant VG effects using each of our productivity measures. These effects may generate non-negligible productivity growth for local firms over the long run. Their magnitudes are estimated to be larger for German than for Italian firms (although the estimates for the German sample are less precise and such difference is not statistically significant). To provide an idea of the magnitude of such an effect, our baseline estimates imply that the presence of foreign-owned firms that were on average 50% more productive than local ones, would induce a long-run productivity gain for local firms of around 8% for a typical German region and around 3% for a typical Italian region. Because the productivity of the average foreign-owned firm was, in some cases, two or even three times as large as the productivity of local firms (at the beginning of the considered period) the VG channel could account for a sizable part of the productivity growth of domestic firms during the 1990s. We interpret this as evidence that the presence of highly productive FDI had a stimulating effect on the productivity of local firms.

The rest of the article is organized as follows. Sections 2 and 3 describe our empirical model and the estimation strategy. Section 4 describes the data for Germany and Italy. Section 5 presents the basic estimates, with particular emphasis on the coefficient that captures the VG effect, and performs several checks of the robustness of these estimates. Section 6 concludes the article.

2. TFP dynamics

We allow the total factor productivity (TFP) of sector s in year t to follow a (deterministic or stochastic) growth path that depends on structural determinants which may vary by sector and year. Calling $A_{i,r,s,t}$ the logged difference between domestic firm i's TFP and the average TFP in sector s and year t, we can describe the dynamics of this variable as follows:

$$A_{i,r,s,t+1} = \beta_1 A_{i,r,s,t} + \beta_2 \bar{A}^{\mathrm{FDI}}_{r,s,t} + \beta_3 \mathrm{FDI\ density}_{r,s,t} + \varepsilon_{it}. \tag{1}$$

In order to capture both persistent firm-specific and region-specific shocks that may affect the long-run productivity of a firm, we assume that the productivity of firm i, $A_{i,r,s,t+1}$, depends on its lagged level $A_{i,r,s,t}$ and on two other factors. One, FDI density$_{r,s,t}$, is the concentration of foreign-owned firms in the same sector and region and is the classic term included to capture spillovers from FDI. It is measured as the share of workers employed in foreign-owned firms in region r and sector s at time t. The other factor, $\bar{A}^{\mathrm{FDI}}_{r,s,t}$ is a measure of the technological level of the foreign-owned firms operating in the same sector and region as domestic firm i. Specifically, we measure it using the average (logged) TFP of foreign firms in region r and sector s for year t. This term captures the scope for the productive catch-up of domestic firms from the technological diffusion provided by foreign firms. Of course we are implicitly assuming that domestic firms have an adequate absorptive capacity,[5] and that geographical proximity enhances spillovers. In the absence of localized spillovers, a homogeneous externality that affects all firms in a sector would not be reflected in the variable $\bar{A}^{\mathrm{FDI}}_{r,s,\mathrm{t}}$ as we control for sector-time effects.

Eq. (1) is a dynamic version of a very common specification used (e.g. by Aitken and Harrison, 1999) to analyze the effects of FDI on domestic firms' productivity. The relevant differences here are the dynamic setting (used to detect effects that materialize with some delay) and the inclusion of the term capturing the average technological level (productivity) of foreign-owned firms operating in region r and sector s.[6]

Several assumptions may justify the presence of this term in Eq. (1). Domestic firms may come in contact with other technologies randomly through a learning process. The geographical proximity of technologies used by foreign firms and their relative quality both speed up the rate of learning for a domestic firm. If we think, for instance, that workers from a domestic firm exchange ideas randomly with workers from foreign-owned firms, the frequency of these exchanges should be negatively related to the *geographic* distance between the firms, while the

[5] For countries with low level of human capital, a measure of average local schooling could proxy their absorptive capacity (see, for example, Keller, 1996, Glass and Saggi, 1998, Kinoshita, 2001). Germany and Italy guarantee adequate levels of literacy and we assume equal absorptive capacity across provinces for a given technological gap.

[6] The theoretical foundation for the dynamic specification can be found in Findlay (1978).

amount of knowledge exchanged should be positively related to the *technological* differences between the firms. This is precisely why highly productive FDI in the same region and sector may boost the productivity of domestic firms. Alternatively, technological gains generated from foreign-owned firms may become local public goods. Then, the localized diffusion of technology and knowledge and the higher quality of such technology result in localized VG effects.[7] While it can be hard to distinguish between specific mechanisms, here we need only identify the overall effect from the empirically measured productivity of foreign firms on the productivity growth of domestic firms.

Assuming that the productivity levels of foreign-owned firms are exogenous to local firms (this is an assumption that we will remove in one of the robustness checks), we estimate Eq. (1) using dynamic panel methods (following Blundell and Bond, 1998). The coefficient β_2 captures the strength of the VG effect (which is the focus of our study) while the coefficient β_3 measures the importance of FDI concentration. As we control for lagged productivity, the regression also provides information on the conditional convergence behavior of a firm's productivity to a common sector-specific growth path. The condition for convergence (stationarity of the $A_{i,r,s,t}$ series) is that the coefficient on lagged productivity, β_1, is significantly smaller than one. In the empirical analysis, we will test for non-stationarity of the variable $A_{i,r,s,t}$ using the test proposed by Bond et al. (2002). The null hypothesis of non-stationarity is always strongly rejected by these tests for all our measures of productivity. Finally, ε_{it} is an i.i.d. random shock. For future reference, we will call the variable $\bar{A}^{\mathrm{FDI}}_{r,s,\mathrm{t}}$ "FDI Productivity". As we control for the lagged productivity of domestic firms with $A_{i,r,s,t}$, the coefficient β_2 captures the beneficial effects of having relatively highly productive foreign-owned firms in the region.

Eq. (1) has several potential advantages relative to the standard approach to FDI spillovers. First, factors that vary with sector and time are fully absorbed into our definition of $A_{i,r,s,t}$, which captures only the productivity difference of a firm from the sector-time average. This is equivalent to absorbing any time by sector effect with a dummy. Second, regional factors that affect TFP levels of both domestic and foreign firms do not bias the estimates of β_2, since that coefficient is identified only on the difference between $\bar{A}^{\mathrm{FDI}}_{r,s,t}$ ("FDI Productivity") and $A_{i,r,s,t}$ (lagged own productivity), both in logs. Third, omitted factors that may attract FDI also should not bias the estimate of β_2 as we control for FDI density$_{r,s,t}$.[8] The effects of these variables are captured by the coefficient β_3. Lastly, this specification enables us to separate a spillover effect from a pure "competition" effect. According to Görg and Strobl (2002), foreign-owned firms drive up wages through their labor demand, and this forces domestic firms to reduce their employment which in turn increases their productivity. Such an effect is likely due mostly to the simple presence of foreign firms (rather than to their productivity) and therefore captured by β_3. Moreover, we can control for this effect by adding the employment growth of domestic firms, thus potentially capturing the elimination of inefficient jobs. We do this in Section 5.4.

[7] An alternative possibility in the case of technology as a local public good is that the relevant productivity gap is between the domestic firm and the most-productive FDI. Work by Griffith et al. (2002) considers this possibility. In practice, however, the measure of the most productive FDI, based on one or few observations only, can be very noisy and less reliable than the average productivity of FDI, since accounting data are biased by the attempt to reduce tax burdens which will particularly affect the tails of the productivity distribution.

[8] Smarzynska Javorcik (2004) modifies this measure by taking into consideration the sectoral input–output structure of the economy to capture backward linkages across sectors.

3. Measuring TFP

In order to estimate Eq. (1), we need to measure the TFP levels of domestic and foreign-owned firms. As TFP cannot be observed directly, it must always be calculated as a "residual" from a production function. Hence, different assumptions concerning the production function, the measurement of factors and estimation methods may produce different TFP evaluations. Here we take the approach of using several different methods to measure $A_{i,r,s,t}$, and we employ each of these measures in estimating Eq. (1). In particular, we use one measure of TFP based on a superlative index (derived from an accounting procedure) and four measures based on production function estimation, two of which are more standard (OLS and fixed effects) and two of which are concerned with non-standard issues (the Levinsohn and Petrin, 2003 method, and the efficient frontier method). The robustness of the results obtained using each approach reinforces our confidence in the estimated effect. We present each of these methods in the rest of this section.

3.1. TFP via superlative index number

Our first measure of TFP uses a superlative index number as derived in Caves et al. (1982). This index assumes a trans-logarithmic production function and constant returns to scale in production, and uses data on factor cost shares (the exact definition of our data is provided in the next section). In particular, we define the TFP level of firm i relative to the average productivity of sector s at time t, $A^{\text{sup}}_{i,r,s,t}$, as:

$$A^{\text{sup}}_{i,r,s,t} = \left(y_{i,r,s,t} - \bar{y}_{s,t}\right) - \frac{\alpha_{i,r,s} + \bar{\alpha}_s}{2}\left(k_{i,r,s,t} - \bar{k}_{s,t}\right). \tag{2}$$

In the expression above $y_{i,r,s,t}$ is the natural logarithm of value added per worker (value of sales net of value of material cost) for firm i in region r, sector s and year t. $\bar{y}_{s,t}$ on the other hand is the average value of $y_{i,r,s,t}$ for all firms in sector s and year t. $\alpha_{i,r,s}$ is the elasticity of output to physical capital of firm i. Assuming constant returns to scale in production and profit maximization behavior, $\alpha_{i,r,s}$ is equal to one minus the share of labor costs in value added for firm i. The parameter $\bar{\alpha}_s$ is one minus the average share of labor costs in sector s. $k_{i,r,s,t}$ is the natural logarithm of capital per worker in firm i in region r, sector s and year t, while $\bar{k}_{s,t}$ is the average of $k_{i,r,s,t}$ for all firms in sector s and year t. Subtracting these averages is equivalent to controlling for sector-time specific effects that may influence TFP. Using this "accounting" method, TFP is actually calculated and not estimated; hence, no standard errors are produced. The only two types of potential errors then are mistakes in the firms' balance sheets, and violations of the theoretical assumptions.

3.2. Total factor productivity via production function estimation

Alternatively, we can identify the relative TFP levels of firms by directly estimating the production function. Here we maintain the assumption of constant return to scale of output to capital and labor.[9] However, rather than rely on cost shares, we directly estimate the elasticity of the value added to capital. We indicate with $A^{\text{prod}}_{i,r,s,t}$ the measure of firm i's TFP in region r,

[9] One of the robustness checks, whose results are reported in Table 6, relaxes the assumption of constant return to scale.

sector s, and year t relative to the sector-year average. In this case, we estimate the following equation:

$$y_{i,r,s,t} - \bar{y}_{s,t} = \alpha_s(k_{i,r,s,t} - \bar{k}_{s,t}) + \beta_s F_{i,r,s,t} + A^{\text{prod}}_{i,r,s,t} + \varepsilon_{i,r,s,t} \tag{3}$$

The coefficient α_s captures the elasticity of output to physical capital and varies by sector, thus allowing for different technologies across sectors. $F_{i,r,s,t}$ is a dummy variable equal to one if the firm is foreign-owned and zero otherwise. Because some firms change ownership during the sample period and indeed may be acquired by multinational corporations, $F_{i,r,s,t}$ for a given firm i may change over time. The coefficients β_s thus capture the effects on productivity from foreign ownership. Like the previous method, sector-time fixed effects are taken into account by "netting" the group mean from each variable.

The term $(A^{\text{prod}}_{i,r,s,t} + \varepsilon_{i,r,s,t})$ accounts for the remaining productivity of firm i. The term $A^{\text{prod}}_{i,r,s,t}$ is that portion of productivity that evolves over time as a state variable, observable to domestic owners and potential (foreign) buyers of the firm. The term $\varepsilon_{i,r,s,t}$ is an i.i.d. zero mean deviation of productivity, unknown to the owner of the firm and to potential buyers. Both terms, however, are unobservable to the econometrician. If $A^{\text{prod}}_{i,r,s,t}$ is the constant productivity advantage (or disadvantage) for firm i, it can be captured using a firm fixed effect φ_i in an otherwise standard panel estimation of Eq. (3). This is what we do when we perform the "fixed effects" estimation. However, if the variable $A^{\text{prod}}_{i,r,s,t}$ varies over time and firms can be purchased with few obstacles by foreign multinationals, the optimal choice of acquisition is likely to be a function of productivity $A^{\text{prod}}_{i,r,s,t}$. This would induce correlation between the terms $A^{\text{prod}}_{i,r,s,t}$ and F_{it}, undermining the consistency of the least squares estimates of α_s and β_s even if we include firm-fixed effects.

The problem of endogenous acquisition of firms is similar to the one of endogenous exit of firms addressed by Olley and Pakes (1996) and Pavcnik (2002), or the problem of endogenous choice of inputs addressed by Levinsohn and Petrin (2003). In our data set, we need to pay particular attention to the endogeneity of acquisitions, which occurred frequently in the 1990s. On the other hand, the sluggishness of the European labor market guarantees that innovations to the variable k_{it} are likely to be uncorrelated with contemporary innovations to $A^{\text{prod}}_{i,r,s,t}$, as it probably takes a firm at least 1 year to adjust its capital and labor inputs.

Our method, a variation on the procedure proposed by Levinsohn and Petrin (2003), relies on the fact that the optimal choice of variable inputs of a firm, such as the material inputs used, m_{it} (for which data are available), depend monotonically on the firm's productivity $A^{\text{prod}}_{i,r,s,t}$, and on its capital per worker k_{it}. Therefore, using the fact that $m_{it} = m(A^{\text{prod}}_{i,r,s,t}, k_{i,r,s,t}.)$ we can invert the function and express $A^{\text{prod}}_{i,r,s,t}$ as the function $A(m_{it}, k_{i,r,s,t})$. Using a polynomial approximation of $A(m_{it}, k_{i,r,s,t})$ we can substitute this function into Eq. (3), absorbing all the variation of the term ${A_{i,r,s,t}}^{\text{prod}}$ in the error and, therefore, eliminating the correlation with F_{it}. This allows us to obtain consistent estimates of the parameters β_s in the first stage of the estimation. Then in a second stage, using the assumption that shocks to the productivity variable, $A^{\text{prod}}_{i,r,s,t} - E_{t-1}(A^{\text{prod}}_{i,r,s,t})$, do not affect either the current capital/labor ratio, $k_{i,r,s,t}$, or the past choice of ownership F_{it-1} we can use this moment restriction to implement a GMM consistent estimator of α_s. The details of this method are described in Levinsohn and Petrin (2003).

The crucial assumption of this approach is that it relies on the contemporary correlation between the use of materials and productivity shocks of a firm in order to "absorb" from the unobserved term the portion correlated with the variable F_{it}, hence providing consistent estimates of β_s. We then use the assumption that capital and labor inputs take a period to adjust to productivity shocks (in contrast to material input use, which adjusts immediately) in order to get consistent estimates of the parameter α_s.

A similar method using investments, rather than material inputs, could be used to correct for the sample selection of firms due to exit, as proposed by Olley and Pakes (1996). Unfortunately, we do not have investment data for the year previous to the one in which a firm exits the data set. Partially mitigating this problem, however, we run some probit regressions of the probability that a firm exits the sample on capital per worker and other firm-characteristics. We do not find any significant relationship with observable variables. Therefore, rather than drastically reducing the sample size in order to include a balanced panel of firms, we simply use the whole sample and assume that the inclusion (or exclusion) in our sample is not correlated with unobserved characteristics that may affect productivity. A final way of estimating total factor productivity relies on efficiency frontier estimation techniques. These techniques estimate the distance of a firm's technology from the production frontier. Essentially, this amounts to the estimation of:

$$y_{i,r,s,t} - \bar{y}_{srt} = \alpha_s\left(k_{i,r,s,t} - \bar{k}_{srt}\right) + \beta_s F_{it} + u_{it} + \varepsilon_{it} \tag{4}$$

where u_{it} follows a truncated normal distribution on the positive range measuring technical inefficiency, and ε_{it} is the usual symmetrically distributed white noise error term.

The term u_{it} is identified as a firm fixed effect with an industry-specific estimated growth trend:

$$u_{it} = u_i \exp(\kappa_s t),$$

where u_i and κ_s and their standard errors are estimated by a maximum likelihood method. The measure of TFP obtained with this method, $A^{\text{front}}_{i,r,s,t}$ is defined as $A^{\text{front}}_{i,r,s,t} = u_{it} + \varepsilon_{it}$.[10] The advantage of this estimation method is that it explicitly assumes the existence of a technological frontier specific to a sector and year and identifies the productivity of firms as their 'relative' distance from this frontier. This is appealing as the local presence of highly productive FDI can be considered a factor which helps a firm catch-up to the technological frontier.

4. The data

We have gathered and organized two new data sets containing balance sheets and accounting and ownership information for a large sample of manufacturing firms in Italy and Germany. The database of Italian firms is an unbalanced panel of about 200,000 observations over the time period 1992–1999. The number of firms included in the sample increases over time and reaches about 40,000 units by 1999. This database includes, in principle, the whole universe of Italian manufacturing firms. However, in the early part of the sample, small firms are under-represented. Thus the coverage of our sample broadens over time. We exclude years 1992 and 1993 from the analysis because missing data from these years comprised too large a fraction of the universe.

The database of German firms covers roughly 2% of all German manufacturing firms and roughly 16% of German manufacturing employment. It is therefore much smaller than the Italian database and concentrates on larger firms. The data consists of an unbalanced panel of about 800 manufacturing firms per year over the time period 1993–1999. However, we check that the data set is representative in the regional and time dimension (a detailed account of this is in Peri and Urban, 2002).

[10] While u_{it} alone is the estimated inefficiency term, the TFP of a plant should also include the zero-mean deviations ε_{it}.

Both data sets use firms as the unit of observation, and balance sheets are the sources of data. This implies that the productive activity is assigned to the headquarters and not to the actual location of plants. In our case, the problem is largely mitigated, because we use unconsolidated balance sheet information both for Italy and Germany. This implies that only plants that are not independent legal entities are mis-classified regionally. As these plants are usually small relative to the headquarters and we are interested in simply the total factor productivity (an average) rather than total volume of activity (a sum), the resulting error is likely to be small.

For the most part we econometrically analyze the Italian and German samples separately, due to some differences in industry codes and regional sizes. However, we do estimate the parameters of interest on the pooled German and Italian data as one of our robustness checks. Given the much larger size of the Italian data set, the results of the pooled regression look similar to those for just he Italian case. The German data capture a particularly interesting period, as the formerly isolated East Germany was suddenly exposed to Western technology and FDI penetration. In contrast, Italy did not experience any major shock during the 1990s, but rather experienced a decade of slow-growth and slow convergence in regional productivity which might have put a particular strain on the less-developed southern provinces. In such conditions, the presence of FDI could have been particularly important for productivity growth in both cases. As the data sets are new, we describe each data set and present summary statistics in the rest of this section.[11]

4.1. Italian firms

Our database of Italian firms, obtained with the assistance of the Centro Studi Luca d'Agliano,[12] merges the AIDA database of Bureau van Dijk (which contains balance sheet information) with the multinational firm database Reprint of Politecnico di Milano (which contains ownership information). The observations on firms' balance sheets include data on the number of employees, wage costs, the value of sales, the value of materials used as intermediates, fixed assets of the company, the industrial sector, the firms' locations and their names. The industry code contains 23 manufacturing sectors. Our definition of region for Italy is the so-called "Provincia," a rather small administrative unit typically containing one main city. There are 103 of these in Italy, which correspond to the "NUTS3" aggregation level in the Eurostat territorial classification.

The summary statistics of the main variables for three representative years within our sample (1994, 1996 and 1998) are reported in Table 1. We define the universe of foreign-owned firms as those firms with a strictly positive fraction of voting rights held by foreigners. Typically, the share of voting rights held by foreigners is large enough to exercise some control of the firm. In 1998, the total employment level for foreign firms was 402,704 employees. The large increase in the number of firms covered by our database from 1994 to 1998, and the decrease in the average size of domestic firms during the same period, are due to the increase in the number of smaller firms included in the sample over time. We eliminate from the data those observations that contain outliers in the levels and growth rates of the firm variables. Appendix A describes the selection procedure in more detail.

Foreign-owned firms tend to have higher value added per worker, to be more capital intensive, and to pay larger wages than domestic firms. On average, therefore, foreign-owned

[11] Further details on the construction of the variables are contained in Appendix A.

[12] We are grateful to Giorgio Barba Navaretti for making this data available to us.

Table 1
Summary statistics for Italian manufacturing firms

Ownership	Foreign			Domestic		
Year	1994	1996	1998	1994	1996	1998
Value added per employee	123.69	128.67	128.61	106.08	110.41	101.88
Fixed assets per employee	99.91	85.18	96.85	77.34	74.39	73.91
Material inputs per employee	314.46	323.77	334.24	305.37	295.65	280.84
Average wage cost/employee	71.48	69.77	70.82	56.66	57.85	56.43
Number of employees per firm	256	332	356	72	62	54
Number of firms	354	898	832	9858	30,469	36,738

Source: AIDA data set, merged with Politecnico di Milano data. Values are in Millions of 1999 Italian Lire. The data set has been purged from outliers and from firms exhibiting unusual changes in capital and employment from one year to the other.

firms tend to have higher labor productivity than domestic firms; this then may be the source of the positive technological spillovers enjoyed by Italian firms. We should keep in mind, however, that the summary statistics presented in Table 1 conceal large differences across sectors and localities. Foreign-owned firms are concentrated mostly in large urban areas in the northwest of the country (mostly Milano, Torino and Genova) and around Rome. They are present, however, in smaller concentrations in most of the provinces. This uneven distribution of FDI is illustrated in Fig. 1. The figure captures with different shades of grey the different percentages of employed workers in foreign-owned firms across provinces. Darker colors correspond to higher FDI concentration. The map also delineates the boundaries of the 103 Italian provinces.

4.2. German firms

Our database of German firms, obtained by retrieving past and current data releases from Bureau van Dijk, is a subset taken from the database Amadeus 200,000 containing only large manufacturing firms with more than 100 employees, more than 10 million Deutsche Marks of total assets, or more than 10 million Deutsche Marks of total sales. This data set contains the same variables as the Italian one, i.e. employment, wage costs, sales, fixed assets, material costs and information on the location, sector and ownership of the firm. For Germany, given the smaller number of firms included in the sample (about 800), we are forced to use a fairly broad regional aggregation, i.e. the 16 Bundesländer,[13] to obtain a sufficient number of domestic and foreign-owned firms in each region. Given the large size of the firms included in the German data set, we believe it appropriate to consider larger regions as the potential receivers of spillovers, since large firms are likely to hire workers and have interactions within a larger “basin of attraction” than smaller firms. Twenty manufacturing sectors (defined according to SIC codes) are included. Three sectors are excluded because of small-sample concerns. We investigate in Peri and Urban (2002) how representative this data is by using aggregate data from Statistisches Bundesamt (2000) and Deutsche Bundesbank (2001) as comparisons. Consistent with the definition used for Italy, we define as foreign-owned any firm which had reported some foreign ownership of their voting shares.[14] We also label Western-owned firms in East Germany as

[13] The Bundesländer correspond to the NUTS1 classification of EUROSTAT.

[14] Of course relevant for determining ownership is the reported primary owner. But if no information is available on the primary owner, the direct ownership determines the nationality of a firm.

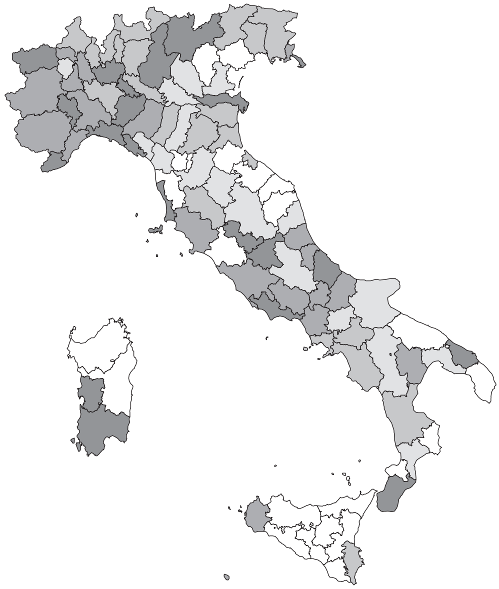

Fig. 1. Concentration of FDI relative to Domestic Firms, Italy 1998. Note: The map shows the concentration of FDI calculated as share of workers employed in foreign-owned firms in a Province in year 1998. The shades of gray (darker shades denotes higher concentration) are five and intervals are spaced so that regions are equally distributed among them (roughly 20 provinces per interval). Data Source: Reprint of Politecnico di Milano.

multinational firms.[15] Companies of Treuhandanstalt, the privatization agency of the German government, are considered local firms.

Table 2 shows the summary statistics relative to three representative years for the German data set. Notice the larger sizes of domestic and foreign-owned firms and their higher productivity and capital intensities relative to Italian firms. Yet even here labor productivity and wages are significantly higher in foreign-owned firms than in domestic ones, confirming that foreign-owned firms enjoy technological advantages over domestic firms.

We construct the variable FDI density$_{r,t}$ as the share of total workers employed by foreign-owned firms in Land r. Data on FDI employment are obtained from Deutsche Bundesbank (2001)[16] and total employment is obtained from Statistisches Bundesamt (2000).[17]

Similar to Italy, the majority of foreign-owned firms are located in large metropolitan areas. Fig. 2 illustrates the density of foreign-owned firms across Bundesländer using darker colors for higher densities. The density of FDI is highest in the Bundesländer containing Berlin, the political center, Frankfurt, the financial center, and Hamburg, the primary port of Germany. While hosting most of the foreign firms, these regions are not necessarily those

[15] Criscuolo and Martin (2002) show that UK-owned multinationals in the UK have the same productivity advantage over UK firms with no plants abroad as foreign-owned multinationals.

[16] We thank Heinz Herrmann of Deutsche Bundesbank for providing this unpublished data.

[17] There are some incompatibilities between Amadeus, the data of Deutsche Bundesbank (2001) and the data of Statistisches Bundesamt (2000) such as the definition of sectors, the definition of FDI and the reporting obligations by firm size.

Table 2
Summary statistics for German manufacturing firms

Ownership	Foreign			Domestic		
Year	1994	1996	1998	1994	1996	1998
Value added per employee	279.52	248.86	296.43	196.65	214.95	239.21
Fixed assets per employee	133.36	149.66	160.18	151.37	181.50	204.76
Material inputs per employee	397.39	392.51	458.43	240.98	275.20	330.39
Average wage cost/employee	91.46	97.50	103.70	82.15	89.23	95.93
Number of employees per firm	1646	1414	1311	1769	1406	1331
Number of firms	203	226	212	653	574	556

Source: Amadeus data set. Values are in thousands of 1999 Deutsche Marks. The data set has been purged from outliers and from firms exhibiting unusual changes in capital and employment from one year to the other.

receiving the largest benefits from these foreign firms. This is because the technological lead of foreign over domestic firms can be smaller in these regions than in less developed regions.

5. Estimation results

5.1. Replicating standard spillover regressions

In this section, we replicate a basic regression used by Aitken and Harrison (1999), among others, in order to investigate spillovers from FDI. Table 3 reports the results from a regression of firm-level output on firm-level inputs (Labor, Capital and Materials) and on FDI density$_{r,s,t}$. The regression only includes domestic firms and assumes a log-linear production function. We report the estimates of the elasticity of output to the three inputs, as well as the effects of FDI density in three specifications for each country. The first three specifications I to III are estimated on Italian data, while specifications IV to VI are estimated on German data.

Columns I and IV include the above-mentioned explanatory variables plus sector and time fixed effects. These regressions yield a significant coefficient on the FDI density variable.[18] This result is qualitatively and quantitatively similar to those obtained in studies of other countries. Thus, FDI density appears to have a positive and significant effect on the domestic firm's TFP.

Columns II and V replace sector fixed effects with firm fixed effects, which renders the coefficients on FDI density insignificant. This is exactly what Aitken and Harrison (1999) found in a similar specification using their data on Venezuelan firms (see their Table 2, specifications 3 and 4). Next, Aitken and Harrison (1999) show that regional control variables such as average regional wage-costs (which proxy for human capital, unobserved differences in labor quality or other location-specific factors) also render the density variable insignificant. We replicate their results in columns III and VI by including average regional wages. We also run a regression that includes regional fixed effects (not reported in the table). In this case, once again the FDI density variable has no significant effect on the productivity of domestic firms. Finally, we allow elasticities to vary by sector, and we include all firms in our regression (domestic and foreign-owned) controlling for ownership. The estimates of the effect of FDI on productivity in those

[18] We use heteroscedasticity robust standard errors rather than clustered standard errors. Despite the problem, pointed out by Moulton (1990), caused by the FDI density variable that is measured at the regional level, our goal here is to keep results comparable with the previous literature that did not apply the clustering correction.

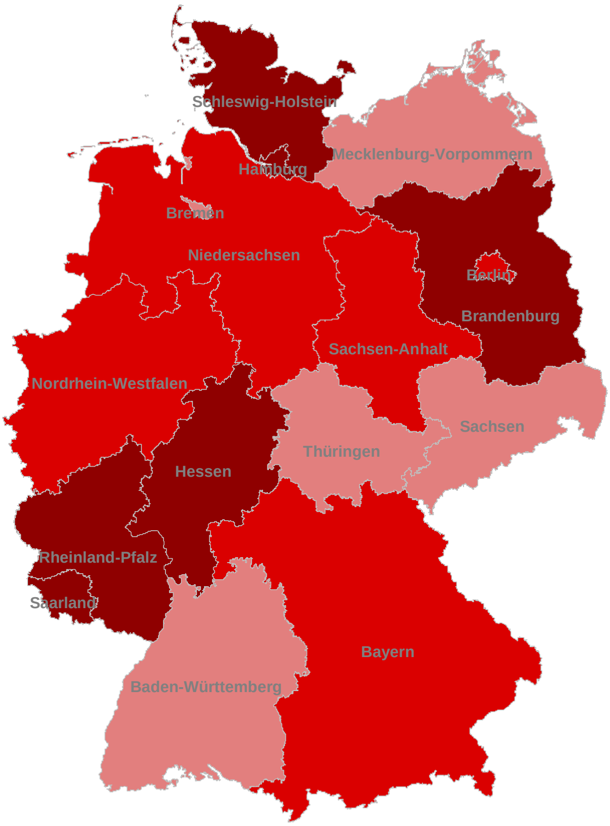

Fig. 2. Concentration of FDI relative to Domestic Firms, Germany 1998. Note: The map shows the concentration of FDI calculated as share of workers employed in foreign-owned firms in a Bundesländer in year 1998. The shades of gray (darker color denotes higher concentration) are three and intervals are spaced so that Landers are equally distributed among them (roughly five Landers per interval). Data Source: Unpublished Data of Deutsche Bundesbank.

specifications (not reported in the table and available upon request) are not significant and very similar to those presented in Table 3.

Summing up, the FDI density variable is positively correlated with the domestic firms' productivity growth at the regional level, but this correlation disappears after controlling for regional characteristics. Regional factors that are responsible for growth may also be responsible for the presence of FDI, inducing a spurious correlation. As we argued above, however, this does not mean that no spillovers result from FDI. Instead, the FDI density variable may not be a good proxy for the intensity of technological spillovers in the first place. In the remainder of this section, we explore the role of the average productivity of FDI in spurring the productivity growth of domestic firms.

5.2. Comparing total factor productivity measures

We estimate the (log of) TFP of a firm, $A_{i,r,s,t}$, using the five methods presented in Section 3. The first method, called "Superlative Index," implements Eq. (2). We use data on the share of wage costs relative to value added, both in each firm and on average, to calculate the elasticity of

Table 3
Standard spillover regressions for Italy and Germany

Country	Italy			Germany		
Specification	OLS	Firm FE	Regional control	OLS	Firm FE	Regional control
	(I)	(II)	(III)	(IV)	(V)	(VI)
$\ln(L_{i,t})$	0.21**	0.21** (0.001)	0.21** (0.001)	0.29** (0.009)	0.25** (0.027)	0.29** (0.009)
$\ln(K_{i,t})$	0.03** (0.000)	0.03** (0.000)	0.03** (0.000)	0.07** (0.005)	0.02** (0.01)	0.07** (0.005)
$\ln(M_{i,t})$	0.75** (0.001)	0.75** (0.001)	0.74** (0.001)	0.62** (0.009)	0.62** (0.030)	0.61** (0.009)
FDI density$_{s,r,t}$	0.03** (0.003)	−0.002 (0.003)	−0.004 (0.003)	0.03** (0.008)	−0.06* (0.03)	0.0006 (0.01)
Average regional wage	–	–	0.002** (0.0001)	–	–	0.002** (0.001)
Sector fixed effects	Yes	No	Yes	Yes	No	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	No	No	No
Firm fixed effects	No	Yes	No	No	Yes	No
No. of observations	162,023	162,023	161,692	3702	3702	3623
R^2	0.98	0.98	0.98	0.97	0.99	0.97

Dependent variable: $\ln(Y_{it})$, natural logarithm of sales of domestic firms.
Heteroscedasticity-robust standard errors in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.

value added to labor (and to capital). This method has the advantage of by-passing any issue concerning the endogeneity of inputs and ownership, since it is not estimation-based; however, it heavily relies on the assumption of constant returns to scale and does not produce a standard error. The remaining four methods are instead estimation-based. In particular, we implement regressions (3) using simple OLS estimation (once the data is cleansed of their time-sector component), estimation controlling for firm fixed effects, or accounting for the potential endogeneity of ownership using the Levinsohn and Petrin (2003) method. Finally, we estimate TFP by using the efficiency frontier estimation procedure and allowing for "firm-specific" inefficiencies.

We report in Tables 4 and 5 the estimated elasticities of value added to capital by industry (parameters α_s of expressions (2) and (3)) for Italy and Germany, respectively, using each of the methods described above. The index-based measures of α_s, reported in the first column of Tables 4 and 5, vary by sector and cluster around 0.4–0.5. This range of estimates seems somewhat large relative to previously estimated elasticities (Pavcnik, 2002, Levinsohn and Petrin, 2003) which, for several manufacturing sectors, range between 0.10 and 0.20. The estimation-based elasticities, reported in columns 2, 3, 4 and 5 of Tables 4 and 5, are much closer to this range. They are also much less variable for a given sector across countries. For these reasons, we tend to prefer the estimation-based measures of TFP which also, as we will see below, produce more stable and precise estimates of the VG coefficient.

In spite of some variation between the results of our different estimation methods, the coefficients obtained using these different methods seem remarkably robust and precisely estimated. Particularly for Italy, thanks to the large size of the sample, most of the

Table 4
Production function parameters estimates for Italy by sector

Estimation method	Superlative index		OLS		Firm fixed effect		Levinsohn–Petrin		Efficient frontier	
Sector (ATECO definitions)	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Food and kindred products	0.47	n.a.	0.22	0.05	0.25	0.01	0.26	0.04	0.22	0.01
Tobacco	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Textile	0.42	n.a.	0.12	0.01	0.15	0.01	0.15	0.01	0.13	0.00
Apparel	0.40	n.a.	0.17	0.01	0.21	0.02	0.21	0.01	0.18	0.01
Leather and shoes	0.38	n.a.	0.17	0.01	0.19	0.02	0.16	0.02	0.18	0.01
Lumber and wood products	0.41	n.a.	0.19	0.02	0.15	0.01	0.19	0.03	0.16	0.01
Paper products	0.44	n.a.	0.19	0.01	0.16	0.02	0.22	0.02	0.17	0.01
Printing–publishing	0.38	n.a.	0.08	0.01	0.17	0.02	0.15	0.02	0.13	0.01
Oil refineries	0.53	n.a.	0.21	0.01	0.16	0.03	0.25	0.06	0.18	0.02
Chemical	0.47	n.a.	0.10	0.01	0.17	0.01	0.23	0.03	0.13	0.01
Plastics	0.43	n.a.	0.17	0.01	0.19	0.02	0.18	0.01	0.18	0.01
Stone, clay, glass, cement	0.40	n.a.	0.16	0.01	0.20	0.01	0.19	0.01	0.17	0.01
Primary metals	0.43	n.a.	0.17	0.01	0.13	0.02	0.11	0.02	0.15	0.01
Fabricated metals	0.38	n.a.	0.14	0.01	0.18	0.01	0.15	0.01	0.16	0.00
Mechanical machinery	0.37	n.a.	0.11	0.01	0.15	0.01	0.07	0.02	0.13	0.00
Computers	0.37	n.a.	0.06	0.02	0.17	0.03	0.05	0.06	0.11	0.02
Electric machinery	0.38	n.a.	0.13	0.01	0.15	0.01	0.09	0.04	0.14	0.01
Communication equipment	0.39	n.a.	0.09	0.01	0.19	0.02	0.17	0.03	0.13	0.01
Precision equipment	0.38	n.a.	0.11	0.01	0.17	0.01	0.19	0.04	0.13	0.01
Auto	0.38	n.a.	0.20	0.01	0.13	0.01	0.14	0.04	0.16	0.01
Other transportation	0.38	n.a.	0.14	0.01	0.16	0.02	0.16	0.05	0.14	0.01
Furniture	0.38	n.a.	0.12	0.01	0.20	0.02	0.20	0.02	0.15	0.00
Repair and recycling	0.46	n.a.	0.27	0.02	0.20	0.04	0.23	0.05	0.18	0.02

The estimated coefficient in each column is the elasticity of value added to the stock of physical capital, assuming constant returns to scale in the production function.
First column: Superlative index numbers, see main text for calculations. Standard error is n.a., because the value is calculated, not estimated.
Second and third columns: OLS and fixed firm effects estimates of the log-linear production function.
Standard errors are heteroscedasticity consistent.
Fourth column: Levinsohn and Petrin (2003) estimates described in detail in the main text. Standard errors are bootstrapped.
Fifth column: Efficient frontier estimates. Estimates described in detail in the main text. Standard errors are bootstrapped.

coefficients in Table 4 are estimated very precisely, and are remarkably close to the estimates from the existing literature. For example, the elasticity of output to capital in the food sector for Italy range between 0.22 and 0.26. The base estimate for the same sector in the US reported by Levinsohn and Petrin (2003) is 0.24. For textiles, our estimates range between 0.12 and 0.15 while theirs is 0.18, and for wood products our estimates range between 0.15 and 0.19 while theirs is 0.19. The standard errors in Table 4 range between 0.01 and 0.03. We compute and report the asymptotically heteroscedasticity-consistent standard errors for the OLS and fixed-effects methods, while for the Levinsohn and Petrin (2003) and efficient frontier methods we report the bootstrapped standard errors. As for the estimated parameters in Table 5, which relate to German firms, some of the standard errors obtained using the Levinsohn and Petrin (2003) method can be quite large. However, except for very few cases, the parameters related to the German sectors are also reasonable and close to the range estimated for Italian firms.

Table 5
Production function parameter estimates for Germany by sector

Estimation method	Superlative index		OLS		Firm fixed effect		Levinsohn–Petrin		Efficient frontier	
Sector (SIC definitions)	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Food and kindred products	0.68	n.a.	0.28	0.03	0.18	0.03	0.20	0.14	0.21	0.02
Tobacco	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Textile	0.45	n.a.	0.12	0.04	0.05	0.04	0.07	0.07	0.09	0.03
Apparel	0.62	n.a.	0.20	0.05	0.11	0.14	0.30	0.17	0.06	0.05
Lumber and wood products	0.45	n.a.	0.20	0.04	0.16	0.05	0.38	0.13	0.18	0.03
Furniture and fixtures	0.46	n.a.	0.07	0.10	0.09	0.12	0.08	0.15	0.10	0.08
Paper products	0.54	n.a.	0.23	0.03	0.20	0.10	0.02	0.09	0.22	0.04
Printing and publishing	0.56	n.a.	0.26	0.09	0.06	0.12	0.04	0.17	0.04	0.04
Chemicals	0.58	n.a.	0.21	0.06	0.01	0.08	0.19	0.16	0.20	0.10
Petroleum refining	0.73	n.a.	0.04	0.02	0.16	0.03	0.09	0.07	0.11	0.01
Rubber and plastics	0.46	n.a.	0.24	0.04	0.52	0.11	0.19	0.20	0.23	0.08
Stone, clay, glass, concrete	0.5	n.a.	0.31	0.02	0.31	0.04	0.23	0.01	0.16	0.04
Primary metals	0.43	n.a.	0.20	0.04	0.13	0.05	0.27	0.09	0.29	0.03
Fabricated metals	0.39	n.a.	0.32	0.01	0.22	0.05	0.22	0.07	0.15	0.02
Industrial machinery and computer	0.42	n.a.	0.20	0.01	0.18	0.03	0.16	0.08	0.11	0.04
Electric machinery	0.43	n.a.	0.15	0.04	0.14	0.05	0.07	0.11	0.19	0.02
Transportation equipment	0.40	n.a.	0.28	0.03	0.28	0.14	0.08	0.15	0.12	0.05
Precision instruments	0.41	n.a.	0.19	0.01	0.18	0.03	0.20	0.04	0.21	0.04
Miscellaneous manufacturing	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Leather products	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

The estimated coefficient in each column is the elasticity of value added to the stock of physical capital, assuming constant returns to scale in the production function.
First column: Superlative index numbers, see main text for calculations. Standard error is n.a., because the value is calculated, not estimated.
Second and third columns: OLS and fixed firm effects estimates of the log-linear production function. Standard errors are heteroscedasticity consistent.
Fourth column: Levinsohn–Petrin estimates described in detail in the main text. Standard errors are bootstrapped.
Fifth column: Efficient frontier estimates. Estimates described in detail in the main text. Standard errors are bootstrapped.

In spite of the relative variation in the estimates of factor elasticities, all the five methods, and particularly the four estimation-based methods, produce TFP estimates that are remarkably similar to each other. Table 6 reports the correlation across observations of these five measures for Italian and German data. The TFP values obtained using the four estimation methods (OLS, FE, Levinsohn and Petrin and efficient frontier) have extremely high correlations with each other, in the range 0.98–0.99. However the index-based values are also highly correlated to the other measures, exhibiting a correlation coefficient of 0.7–0.8. This reassures us as we interpret each of these measures as a proxy for the actual productivity of a firm.

5.3. Evidence on the VG effect

In this section, we estimate specification (1) in order to capture the spillover effects from foreign-owned firms. We use the Blundell and Bond (1998) one-step system GMM estimator, which improves the efficiency on the Arellano and Bond (1991) GMM difference estimator (especially in panels with short-time dimension) by using past levels as well as time differences to instrument the lagged level of firm TFP. This method provides consistent coefficient estimates

Table 6
Correlation between different TFP measures

	Superlative index	Levinsohn–Petrin	FE	OLS	Efficient frontier
Italian firms					
Superlative index	1				
Levinsohn–Petrin	0.841	1			
FE	0.859	0.998	1		
OLS	0.799	0.994	0.991	1	
Efficient frontier	0.821	0.997	0.996	0.999	1
German firms					
Superlative index	1				
Levinsohn–Petrin	0.708	1			
FE	0.713	0.976	1		
OLS	0.723	0.981	0.974	1	
Efficient frontier	0.716	0.984	0.987	0.993	1

The measures of firm-level TFP are calculated in differences from the sector-period. Each method is described in detail in the text.

(as opposed to OLS or fixed effects procedures that produce biased estimates in panels in the presence of correlation between the lagged dependent variable and the error term). The GMM estimates on Italian data are based on a restricted set of instruments, while the German estimates employ all independent variables, along with lagged and lagged differences of the independent variables as instruments. The dynamic panel estimations include firm random effects.[19]

The results of the dynamic panel estimations are reported in Table 7 for Italy and in Table 8 for Germany. Each column of each table uses a measure of productivity obtained from one of the five different methods described above. The reported standard errors are heteroscedasticity and autocorrelation consistent. Still, the GMM-estimator assumes no autocorrelation of second order or higher. A second order AR-test (AR2) investigates this assumption. Finally, the validity (exogeneity) of instruments is tested using a heteroscedasticity consistent Hansen J-test. In principle, the Blundell-Bond estimator is still consistent when the data are non-stationary, but Binder et al. (2003) show that small sample properties become unfavorable. Therefore, we apply a simple test suggested by Bond et al. (2002) to test for unit roots in our data. We are able to reject the null hypothesis of non-stationarity for each of the variables included in our regressions. The test statistics are reported in Appendix A. Moreover, all the auxiliary AR2-tests cannot reject the assumption of no autocorrelation of order two at the 5% level and no Hansen J-test rejects the assumption of exogeneity of instruments at the 5% confidence level in both tables. Therefore, exogeneity of lagged differences and of the instruments cannot be rejected.[20] The coefficients of interest are those on the "FDI-Productivity" variable ($\bar{A}^{\mathrm{FDI}}_{r,s,t-1}$) and on the density of multinationals in the regional industry, (FDI density$_{rst}$).

The first result which consistently emerges from all the estimates of Tables 7 and 8 is that the "FDI-Productivity" variable always has a positive and significant effect (mostly at the 1% level and occasionally at the 5% level) on the productivity growth of domestic firms. This is true for both Italian and German firms for each single measure of productivity. This implies that the coefficient β_2 of Eq. (1) is positive and significant, and that the productivity gap between local

[19] We thank David Roodman for providing us with the STATA program xtabond2. Of course, we take full responsibility for the accuracy of all calculations.

[20] One caveat remains: The Hansen J-test is extremely sensitive to small changes in specifications in the case of Italy.

Table 7
Dynamic panel estimation, basic specification, Italy

Productivity measures	Superlative-index	Firm fixed effect	OLS estimates	Levinsohn–Petrin	Efficient frontier
Specification	Blundell-Bond estimator				
$A_{i,s,r,t}$	0.33**	0.15** (0.02)	0.12** (0.02)	0.14** (0.02)	0.13** (0.02)
FDI productivity	0.03** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)
(FDI density)$_{r,s,t}$	0.08** (0.04)	0.13** (0.04)	0.13** (0.04)	0.13** (0.04)	−0.03 (0.03)
Sector/year-effects	Yes	Yes	Yes	Yes	Yes
Number of observations	32,462	36,057	36,057	36,057	36,123
AR(1)-Test	−29.14**	−29.32**	−27.22**	−28.81**	−28.82**
AR(2)-Test	1.40	0.91	0.53	0.67	0.68
Hansen J-test (p-value)	2.20 (0.53)	7.19 (0.07)	6.71 (0.08)	7.45 (0.06)	6.80 (0.08)

The dependent variable, $A_{i,s,r,t+1}$ and the explanatory variable $A_{i,s,r,t}$ are TFP of firm i in region r and sector s for year $t+1$, and t, respectively. They are "netted" of the year-sector specific average.
Each column uses TFP measures calculated according to a different method.
FDI productivity: Average productivity of a foreign-owned firm in region r and sector s in year t. Strict exogeneity assumed.
(FDI density)$_{r,s,t}$: Share of workers employed by foreign-owned firms in region r and sector s in year t. Strict exogeneity assumed.
AR(2)-Test: Test statistics for second order autocorrelation of the error terms.
Hansen J-test: Test of overidentifying moment restrictions.
Errors in parenthesis are heteroscedasticity consistent.
** Significant at the 5% level.

multinationals and the domestic firms acts as a growth-promoting factor, revealing a positive VG effect. Such a positive effect does not stem from any productivity "catch-up" due to general convergence, because we control for the level of lagged productivity, $A_{i,r,s,t-1}$. We estimate a positive effect of local catch-up due to the presence of highly productive foreign firms above and

Table 8
Dynamic panel estimation, basic specification, Germany

Productivity measures	Superlative-index	Firm fixed effect	OLS estimates	Levinsohn–Petrin	Efficient frontier
Specification	Blundell-Bond estimator				
$A_{i,s,r,t}$	0.27**	0.31** (0.09)	0.31** (0.10)	0.31** (0.10)	0.31** (0.10)
FDI productivity	0.17** (0.08)	0.11** (0.05)	0.12** (0.05)	0.10** (0.05)	0.10** (0.05)
(FDI density)$_{r,s,t}$	1.77** (0.77)	1.17 (0.70)	1.06 (0.64)	1.08 (0.69)	1.07 (0.68)
Sector/year-effects	Yes	Yes	Yes	Yes	Yes
Number of observations	1236	1285	1291	1225	1291
AR(1)-Test	−1.57	−2.79**	−2.70**	−2.59**	−0.24
AR(2)-Test	−0.95	−0.29	−0.37	−0.39	−0.15
Hansen J-test (p-value)	24.55 (0.17)	18.9 (0 .46)	20.66 (0.37)	20.20 (0.38)	20.43 (0.36)

The dependent variable, $A_{i,s,r,t+1}$ and the explanatory variable $A_{i,s,r,t}$ are TFP of firm i in region r and sector s for year $t+1$, and t, respectively. They are "netted" of the year-sector specific average.
Each column uses TFP measures calculated according to a different method.
FDI productivity: Average productivity of a foreign-owned firm in region r and sector s in year t. Strict exogeneity assumed.
(FDI density)$_{r,s,t}$: Share of workers employed by foreign-owned firms in region r and sector s in year t. Strict exogeneity assumed.
AR(2)-Test: Test statistics for second order autocorrelation of the error terms.
Hansen J-test: Test of overidentifying moment restrictions.
Errors in parenthesis are heteroscedasticity consistent.
** Significant at the 5% level.

beyond this mechanism. Moreover, by construction, the variable $A_{i,r,s,t}$ is cleansed of all time-sector fixed effects so that the correlation between the productivity gap and domestic firm growth cannot be due to either any sector-specific business cycle effect or FDI concentration in certain sectors.

Quantitatively, the VG effect is larger in size for German than for Italian firms. An increase in the productivity of foreign firms by 50% in a German region would induce a productivity increase for domestic firms by 5–6% in the short run (within a year) and by 7–8% in the long-run.[21] A similar increase of FDI-induced productivity in Italy generates a short-run gain of productivity for domestic firms of 2% and a long-run gain of 3%. The VG effect for Italian firms is 20–30% of the size of that for German firms; however, due to the larger sample size, it is more precisely estimated. The fact that eastern German firms were the first to be exposed during the sample period to more advanced western technologies and western competition may have forced them to catch-up faster (captured by the large VG effect), not only improving their technology but also reducing inefficiencies and increasing utilization. Italian firms, on the other hand, may not have been under these pressures.

Another result emerging from our estimates is that the density of foreign-owned firms in the sector-region generally has a positive effect on the productivity growth of domestic firms, but this is often imprecisely estimated, especially for German data. When the effect is significant, however, it is positive. As argued above, this weak effect may reflect the fact that FDI is most concentrated in the urban centers of economic activity, where the productivity of domestic firms is already high and hence less affected by technological spillovers. In contrast, the larger productivity gap with foreign-owned firms in less developed regions is the main cause of technological catch-up, even if the density of FDI is not particularly large.

Finally, each specification estimates the coefficient β_1 as significantly smaller than 1. This ensures the conditional convergence of a firm's productivity to a common sector-year growth path. Given the size of the coefficient (around 0.3 for Germany and between 0.15 and 0.3 for Italy) this convergence proceeds rather quickly.[22] Therefore, our estimates can be interpreted as follows: while some sector-specific technological factors determine the common rate of productivity growth, firms in close proximity to highly productive FDI tend to converge to higher relative productivity levels, since they greatly benefit from technological transfers. The concentration of foreign firms in the sector/region seems to have a less significant (and imprecisely estimated), albeit generally positive, effect on the relative productivity of domestic firms. The productivity advantage of foreign firms, on the other hand, has a consistent and significantly positive impact on the productivity of domestic firms. This is consistent with local technological spillovers that depend on the "technological gap" between FDI and domestic firms, rather than simply on the density of FDI. As found above, FDI can be concentrated in advanced regions, where there is not much scope for technological learning, while fewer but highly productive foreign companies can have a strong domestic impact in less-developed regions.

[21] Given the dynamic Eq. (1), the short-run effect on $A_{i,r,s,t}$ of higher productivity of FDI is captured by the coefficient β_2 while the long-run (balanced growth path) effect is given by $\beta_2/(1-\beta_1)$.

[22] Unlike convergence in the macroeconomic growth literature, convergence of productivity of firms is driven by market competition. Firms that fall below the efficiency frontier need to catch up quickly to avoid bankruptcy.

Table 9
Estimates of the Veblen–Gerschenkron coefficient, robustness checks

Country	Italy		Germany	
Method to calculate the TFP	FE	Levinsohn–Petrin	FE	Levinsohn–Petrin
(1) Blundell-Bond omitting FDI density	0.02** (0.01)	0.02** (0.01)	0.10** (0.04)	0.09** (0.04)
(2) Two-step GMM estimator	0.02** (0.01)	0.02** (0.01)	0.04 (0.04)	0.06 (0.05)
(3) Endogeneity of FDI productivity	0.04** (0.01)	0.04** (0.01)	0.10** (0.05)	0.13** (0.06)
(4) Controlling for employment growth	0.02** (0.01)	0.02** (0.01)	0.09** (0.04)	0.08* (0.05)
(5) Not imposing CRS in production	0.02** (0.01)	0.02** (0.01)	0.18** (0.07)	0.11** (0.05)

Each cell shows the coefficient and standard error of the variable FDI productivity in a different regression. S.E. in parentheses are based on cluster covariance matrix.
Specification (1): Basic specification using the Blundell-Bond efficient one-stage estimator without FDI density. Asymptotic standard errors in parenthesis.
Specification (2): Basic specification without including the variable FDI density and applying two-stage efficient GMM estimator. The standard errors are computed using the Windmeijer (2000) correction.
Specification (3): Estimates performed allowing the FDI productivity variable to be pre-determined rather than strictly exogenous. The variable is instrumented using its lags.
Specification (4): Basic specification using the Blundell-Bond efficient estimator and including employment growth as explanatory variable at the firm level. Employment variable assumed pre-determined (not strictly exogenous).
Specification (5): The TFP estimates in the first stage of the econometric procedure have been obtained without imposing constant returns to scale (in capital and labor) of the production function.
* Significant at the 10% level.
** Significant at the 5% level.

5.4. Robustness of the VG effect

We perform several robustness checks of these results. Our main goal is to confirm that the VG effect from FDI remains positive and significant to changes in the specification, method of estimation and inclusion or exclusion of control variables. We summarize these robustness checks in Table 9 by reporting only the estimates and the standard errors of the coefficient on the "FDI-Productivity", for this captures the intensity of the VG effect and has been the focus of our analysis throughout the paper. In the interest of brevity, we report only those specifications that use TFP measures based on the fixed effect estimation (FE) and the Levinsohn and Petrin (2003) (Lev. Pet.) methods. The remaining "estimation-based" methods (OLS and frontier) produce very similar results. As for measures based on the superlative index, they also generate similar results, but due to the larger variability of this measure the VG effect is often less precisely estimated and only marginally significant, especially in the German case.[23] Columns 1 and 2 of Table 9 report the coefficient estimates using Italian data, while columns 3 and 4 report the estimates using German data.

Specification (1) reports the estimates from specifications identical to those in columns 2 and 4 of Table 7 (for Italy) and Table 8 (for Germany) excluding the FDI-density variable. Because this variable was not significant in several specifications, we check that its omission does not alter significantly the estimated VG effect. It is clear from the reported results that the inclusion or exclusion of that variable does not make any difference. This reinforces our theory that the relevant variable in capturing FDI spillovers is their productivity rather than their regional density. Specification (2) uses an efficient two-step GMM procedure by weighting the moment conditions by a consistent estimate of their covariance matrix in the

[23] The results of robustness checks for all methods are available from the authors upon request.

second step. This method increases the asymptotic efficiency of the estimator; however, it may be biased in small samples. In particular, the estimates of the covariance matrix can be significantly biased due to the inclusion of the estimated coefficients in the weighting matrix. We correct for this bias in the covariance matrix by using the adjustment method proposed by Windmeijer (2000). While the estimates are very close to those obtained using the basic Blundell and Bond estimator for Italy, they are somewhat smaller and less significant for Germany. Due to the small size of the German sample, we believe that the decrease in the point estimate may simply result from the small sample bias of this method. In specification (3), we substitute the assumption that the productivity of FDI in a region is exogenous with the weaker one that it is pre-determined. Namely, its change in the present period is allowed to correlate with the residual of the regression; however, its level in the previous period is not. In this case, we need to instrument the variable using its lags. The point estimates of the VG effect obtained using this specification are somewhat larger for Italy and remain unchanged for Germany. We detect no significant sign that FDI productivity is endogenous.

In specification (4), we include the change in the firm's employment as a control to check whether the positive catch-up effect by local firms was simply achieved by trimming inefficiently employed workers (i.e. through a decrease in employment). While productivity growth has a significantly negative association with employment growth (revealing in equilibrium the potential effects of workers' selections on productivity growth), the Veblen–Gerschenkron effect is still positive and significant, while little else changes. For German firms the coefficient estimates are between 0.08 and 0.09 (standard errors 0.04–0.05) while for Italian firms these estimates are close to 0.02 (standard errors 0.01).

In specification (5), we perform a more demanding robustness check by re-estimating the TFP measures without imposing constant returns to scale (CRS) in the firm's production function.[24] The estimates of the elasticity of output to capital (not reported) obtained without imposing CRS are often quite different from our previous estimates. Moreover for some sectors formal tests reject the assumption of constant returns to scale (mostly in favor of decreasing returns to scale). Remarkably, however, the TFP measures obtained in this more general case are still highly correlated to those previously estimated. Moreover, the estimates of the VG effect essentially mirror those estimates from the previous specifications for Italy (coefficient of 0.02 and standard error of 0.01) and maintain the same range for Germany (coefficients between 0.11 and 0.18 and standard errors between 0.05 and 0.07).

Overall, these robustness checks confirm the existence of a positive and significant VG effect, larger in size for Germany than for Italy, and stably estimated across specifications. We also perform for each specification (not reported) the Hansen *J*-test of exogeneity of instruments as well as the auxiliary AR-1 and AR-2 tests. While most of the time we could reject endogeneity of the predetermined variables at the standard levels of significance, in some isolated cases that test fails to reject endogeneity. However, as the magnitude and significance levels of the estimated coefficients hardly vary across specifications, particularly for the more precise estimates for Italy, we regard the overall evidence as favorable to the existence of robust Veblen–Gerschenkron effects.

While the point estimates of the VG effect for Italy and Germany are somewhat different, a formal test cannot reject that the coefficients for Italy are actually equal to those for

[24] This robustness check can be performed using only estimation-based methods. The superlative index method requires us to assume constant return to scale in production as an identifying assumption.

Table 10
Pooled estimates on German and Italian data, Veblen–Gerschenkron coefficients restricted to be the same across countries

Productivity measures	Superlative-index	Firm fixed effect	OLS estimates	Levinsohn–Petrin	Efficient frontier
Specification	Blundell-Bond estimator				
(1) Restricted VG coefficient basic specification	0.04** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)
(2) Restricted VG coefficient omitting FDI density	0.04** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)
(3) p-value of test that VG coefficients are equal in unrestricted regression	0.24	0.80	0.65	0.90	0.95
Sector/year-effects	Yes	Yes	Yes	Yes	Yes
Number of observations	33,774	37,423	37,421	37,355	37,328

Each cell shows the coefficient and standard error of the variable FDI-productivity from a different regression.
Row (1) shows the estimate of the coefficient on FDI-productivity from a pooled regression as in the basic specification of Tables 7 and 8. All coefficients are allowed to be different between countries, except for the reported one which is constrained to be equal.
Row (2) reports same estimates as (1) obtained from a pooled regression in which the variable FDI density is omitted.
Row (3) shows that the p-value of the test of equal coefficients on FDI between countries against the alternative of different coefficients. The null of equal coefficients between countries is never rejected at any significance level. This implies that the restriction used to estimate rows (1) and (2) is not rejected by the data.
** Significant at the 5% level.

Germany. The larger (but less precisely estimated) effect for Germany could be a consequence of the sudden East German exposure to technological transfer channeled through locally established western firms. Italy, to the contrary, exhibits a positive but smaller effect as FDI continues to exert a beneficial effect on the productivity of local firms, but here there are no sudden gains from openness. However, the difference in point estimates may simply stem from a lack of precision, driven mainly by the small sample size of the German data. In order to improve the precision of these estimates, we may pool the data for Italy and Germany. Due to large differences in sample sizes, however (the Italian firms are almost twenty times as many as the German ones), a pooled sample will naturally be heavily influenced by changes in Italian data. Nevertheless, as a check, we run the pooled regression and report the results in Table 10. We estimate Eq. (1) on the pooled sample, allowing all dependent variables, except for FDI productivity, to have different coefficients between the two countries. Row (1) of Table 10 reports the Blundell-Bond estimates of the VG effect in the basic specification, using each measure of TFP. Row (2) reports the results when omitting FDI density from the regression. The coefficient estimates are precise and very close to those obtained for the Italian sample. Allowing the VG coefficient to vary between countries, a formal test (reported in row (3)) cannot reject the hypothesis that the coefficients are equal across countries. The pooled results confirm the existence and significance of the VG effect.

6. Conclusion

Technological catch-up is a powerful force behind the development of regions and countries, and is likely an important force for convergence in incomes per capita across

OECD countries. FDI is often considered a channel of diffusion of technological knowledge. It seems natural, therefore, to inquire whether the impact of FDI on the productivity of local firms works through a catching-up mechanism that depends on geographical proximity and/or on the technological gap. Surprisingly such a study had not yet been done. Our article uses two new data sets of Italian and German firms to test this hypothesis. Rather than the usual specification in which the presence of FDI has an effect on local productivity, we test the more detailed hypothesis that the technological edge of foreign firms, coupled with the proximity in location and similarity in specialization, helps local firms to grow faster. The technological advantage enjoyed by foreign-owned firms is better captured by FDI's average productivity in a sector-region rather than FDI's concentration in a sector-region. Our empirical test confirms this theory and finds a significant positive effect of FDI productivity on local firms' growth. As our story is based on productivity catch-up we implement several different methods to measure firms' TFP, each with their own advantages and limits. This also is a relatively original contribution and, in our case, it establishes that index-based measures of firm-level productivity are highly correlated with estimation based measures. In particular, the simple cost-based superlative index or the simple fixed effects estimation of the production function produce quite similar results relative to other more sophisticated methods that account for firm heterogeneity or for the potential endogeneity of foreign ownership.

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Appendix A. Data description

A.1. Italian firms

Firm data are from the database AIDA of Bureau van Dijk and are matched with ownership information from the FDI database of Politecnico Milano. Only manufacturing firms are included if they report information on a two-digit industry code (ATECO), the province location of the firm headquarter, and a dummy for foreign ownership participation. Ownership information is collected biannually and assumed to be persistent in a year previous to a reporting year. Whenever available, unconsolidated balance sheet data are used to avoid as much as possible multi-plant firms, which may produce in regions other than the one where the headquarter is located. In general, Bureau van Dijk does not apply any exclusion criteria. However, very small enterprises appear under-represented. Moreover, the database is growing over time. While in the initial years only large firms are sampled, there is no apparent systematic pattern according to which sampling is enlarged until the data set reaches its full size.

To control for outliers and to keep the database homogenous, we exclude a number of observations according to the following criteria:

1) Observations for which capital stocks or sales data were reported as 0 were excluded; observations for which material costs were larger than sales were excluded; observations for which gross operating profits (sales minus material cost minus wage costs) are larger than 80% of sales value or smaller than -80% were excluded. Firms with less than 500,000 Lira per employee fixed assets and more than 3 billion Lira per employee were excluded. These exclusion criteria eliminate outliers.
2) All observations with value added divided by sales smaller than 10% were excluded. These firms are considered sales firms that are mis-classified by Bureau van Dijk as production units.
3) All observations with growth rates of employment, fixed assets per employee, material, and average wage cost per employee[25] of more than 400% or less than minus 80% per year were excluded; These criteria ensure that the structure of a firm does not change largely due to re-organization, re-grouping, or takeovers and firm sales within holding companies;
4) All firms with less than 5 employees were excluded. These firms are too small to be considered manufacturing firms.
5) For superlative index based estimations observations with a labor cost share in value added of more than 0.99 or less than 0.01, and average wage costs per employee (and year) of less than 10 million Lira and more than 500 billion Lira were also excluded. Some average wage cost data may be flawed, since there may be a mismatch between the date of reporting of employees and the period over which wage costs are added. Also, restructuring of firms during the reporting period may be a cause for outliers.
   Finally, part-time work is not appropriately counted. Reassuringly, however, while the "cleaning" of the data reduces the sample by about 20% (from 209,934 to 166,550 observations) our coefficient estimates are not sensitive to the exclusion criteria.

We checked representativeness, using ISTAT census for 1996 and 1991. Unfortunately, the industry codes of the census and of our firm database are incompatible so that we can only compare the regional dimension. In 1996, our firm database covers 56% of manufacturing employment and its distribution across provinces calculated using our firm database or ISTAT census data is very similar (correlation of 0.93).

Appendix B. German firms

Firm level data are from the Amadeus 200,000 database of Bureau van Dijk. This database is updated in real time on-line. We took data in March 2001. Bureau van Dijk eliminates all observations which are older than 5 years. We completed the data set by using an old CD-ROM from 1999.[26] The firm matching between the two data files is incomplete, because the firm identification code changed slightly in some cases. We have made a case-by-case evaluation if in doubt. We have also run consistency checks on location information and adjusted 43 observations. All firms without ownership information in the data set are considered local

[25] The wage cost exclusion criterion applies only to superlative index based estimations.

[26] We thank Bocconi library for providing us with these data and Bureau van Dijk, office Milan, for giving us special permission for the use of these data.

owners. This is common practise for the database. Ownership information is available but not in every year. We assume that ownership status is persistent in the years previous to reporting and only changes at the year of reporting. Foreign-owned firms are firms with reported voting rights accruing to at least one ultimate foreign owner. This typically implies a substantial (but not necessarily a majority) share of voting right in foreign hands. For East German firms, Western owners are considered as foreigners. Companies of Treuhandanstalt–the East German privatization agency–are considered domestically owned. Unconsolidated balance sheet data are used.

The same exclusion criteria that was applied to the Italian data were also applied for the German data.[27] We exclude, however, all firms with less than 20 employees (rather than 5). As the Amadeus database excludes small firms, those with less than 20 employees are most likely holding companies with large assets and no production workers. Even for Germany, the coefficient estimates are not sensitive to changes in the exclusion criteria. Reported industry codes are US-SIC codes. We include only manufacturing firms with US-SIC codes 20–39. All observations without US-SIC code are eliminated. In addition, we exclude for the dynamic panel estimations all sectors with less than 35 observations (SIC21, SIC31, SIC39) to have a reliable sector-specific estimate of the capital share used in TFP calculation.

We also investigated, in greater detail, the representativeness of our German database. Tables and statistics relative to the comparison of our data with Bundesbank data are available from Peri and Urban (2002). Here it is enough to note that the number of sampled firms in our database is rather stable over years (around 800 firms sampled each year), reducing the problem of attrition. Also, while some sectors are over-represented (such as chemicals) due to the larger average size of their firms, the coverage of our database is close to be representative at the regional level.

Appendix C. Panel unit-root tests

Coefficient estimates in panels with a short and fixed time dimension using the Arellano and Bond (1991) method are inconsistent if data have a unit-root, while the Blundell and Bond (1998) estimator would have poor small-sample properties (see Binder et al., 2003) with non-stationary data. For this reason, we perform a test of unit-root on each measure of productivity and on other variables used in the empirical analysis. Bond et al. (2002) suggest to use the t-statistic from a simple OLS estimator (with clustered standard errors) of the variable on its lagged level, $x_{it}=\beta x_{it-1}+\varepsilon_{it}$. As the estimate of the coefficient on the lagged level is consistently estimated and equal to 1 under the null-hypothesis of a unit root, but inconsistently estimated under the alternative hypothesis of a stationary time series, the test statistic $(\beta_{\mathrm{OLS}}-1)/\mathrm{S.E.}_{\mathrm{OLS}}$ is distributed as a standard normal (with zero mean and standard deviation equal to 1) under the null. Based on Monte Carlo evidence this test performs well even in the case of a short-time dimension. Using this test, we can reject the null hypothesis of unit roots for all variables used in our study. The values of the test statistics for each variable and the marginal probability of rejecting the null when it is true for each variable and data set are reported in Table A1.

[27] Nominal values of exclusion criteria are translated with an implicit exchange rate of 1 DEM equal to 1000 Lira.

Table A1
Unit-root tests

Country	Italy		Germany	
Variable name	Test-statistic	Marginal probability[a]	Test-statistic	Marginal probability
A_{it}^{sup}	−90.1	<0.01	−5.83	<0.01
A_{it}^{FE}	−91.1	<0.01	−7.43	<0.01
A_{it}^{OLS}	−71.1	<0.01	−7.55	<0.01
A_{it}^{LP}	−92.3	<0.01	−7.43	<0.01
A_{it}^{Front}	−90.2	<0.01	−7.44	<0.01
$\bar{A}_{r,s}^{\mathrm{FDI,sup}}$	62.5	<0.01	−11.4	<0.01
$\bar{A}_{r,s,t}^{\mathrm{FDI,FE}}$	−90.2	<0.01	−8.89	<0.01
$\bar{A}_{r,s,t}^{\mathrm{FDI,OLS}}$	−74.3	<0.01	−9.67	<0.01
$\bar{A}_{r,s,t}^{\mathrm{FDI,LP}}$	−72.1	<0.01	−8.96	<0.01
$\bar{A}_{r,s,t}^{\mathrm{FDI,Fron}}$	−74.2	<0.01	−9.65	<0.01
FDI density$_{r,s,t}$	−41.2	<0.01	−8.12	<0.01
ΔEmployment$_{it}$	−34.2	<0.01	−22.75	<0.01

[a] Marginal probability of rejecting the hypothesis of unit-root when it is true.

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