Microfounding regional disparities through productivity dynamics

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Abstract

We provide a methodological framework nesting plant-level productivity estimates within a regional dimension, thus recovering a microfounded decomposition of the sources of regional disparities. At this purpose, we exploit a dataset of some 7,800 domestic firms and 3,200 affiliates of Multinational Enterprises (MNEs) operating in the eight administrative regions of Romania for the period 1995-2001. We find that MNEs, contrary to domestic firms, positively contribute to regional output via higher increases in productivity, deeper restructuring and faster net entry dynamics, however at the cost of an increase in regional disparities, since the effects of MNEs are unbalanced across regions. Nevertheless, regional disparities are likely to be a short term phenomenon, since we can rule out a structural negative effect of multinationals on the productivity of domestic firms.

JEL classification: F12; F23; L10; P20

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1 Introduction

The persistence of income disparities across countries or regions has been a major topic of discussion in the field of economics in the recent years. Standard neoclassical economic theory suggests that, under diminishing returns and free movement of factors, per capita income levels within an economic area should converge over time to the same steady state value (Barro and Sala i Martin, 1991). However, such a view has been challenged by many authors (e.g. Durlauf and Johnson, 1995 or Quah, 1996, to quote the early contributions) which, using various econometric methods, have found a persistence of income disparities, arguing therefore that the pattern of cross-country growth is more consistent with endogenous growth, rather than neoclassical theories.

Apart than measuring convergence (or divergence), the literature has also explored the sources of convergence and, more in general, of aggregate growth. Bernard and Jones (1996) measured the convergence of sectoral productivity in different industries with respect to aggregate productivity in a panel of fourteen OECD countries, finding no sign of convergence in manufacturing. A large strand of literature has instead used firm-level data to explore the connection between micro productivity dynamics and aggregate industry growth, in both developed and developing countries\(^1\). In a later contribution, Kumar and Russell (2002) have employed non parametric production-frontier techniques to decompose international macroeconomic convergence (measured as labor productivity growth across countries) into components related to technological catch-up, technological progress and capital deepening.

However, to the best of our knowledge, no study insofar has explicitly looked at how firm-level productivity dynamics affect the evolution of income disparities at the (macro) regional level. The goal of this paper is thus to develop a methodological framework able to appropriately measure and aggregate plant-level productivity estimates in order to identify the micro-foundations of regional disparities\(^2\).

The question is particularly relevant from a methodological point of view, since it would allow us to start bridging the current gap existing between the industrial organisation literature studying firm-level productivity dynamics and the macro literature on the sources of aggregate growth, thus better understanding the channels that drive the emergence, persistence or reduction of income disparities. In addition, the question is also relevant from a policy point of view, since for highly integrated economic areas like the US or the EU, understanding the sources of regional disparities in order to correct them has always been at the heart of the policy-making


\(^2\) The same methodology could be applied to cross-country estimates, provided that comparable firm-level datasets, able to track the aggregate evolution of output at the country level, are available.
debate\textsuperscript{3}.

To explore these issues, Section 2 presents a brief critical review of the empirical literature on regional disparities, and the relations emerging between this field and the literature on productivity dynamics. Section 3 introduces the methodological framework through which it is possible to nest plant-level productivity estimates within a regional dimension, thus recovering a micro-founded decomposition of aggregate output growth at the regional level. Section 4 discusses our dataset and the main results of our decomposition in terms of regional disparities, while Section 5 explores through an econometric exercise the determinants of some of the identified sources of regional output changes. Section 6 concludes.

2 Income disparities and productivity at the regional level

The traditional approach used to measure regional disparities, known as $\beta-$convergence, is to regress the average growth rate of the per capita income of a given region $i$ with respect to its initial value, controlling for some variables which proxy for regional differences\textsuperscript{4}. The works of Canova and Marcet (1995) and De la Fuente (2002), to mention just two of a large set of contributions, have confirmed by and large the convergence of regional incomes to different steady states, generating a persistence of regional disparities, in line with the previously quoted studies conducted at the country level\textsuperscript{5}.

In terms of sources of regional disparities, the mechanisms other than diminishing returns identified by the literature as critical for (conditional) convergence are the technological diffusion (Keller, 2002) and the structural change through the reallocation of productive factors across sectors (De la Fuente, 2002). For example, Boldrin and Canova (2001) show that most of the regional income differences in their EU sample of regions can be attributed to differences in total factor productivity (TFP), and not to differences in per worker capital stocks. Multinational enterprises (MNEs) do also play an important role in the picture via spillovers and reallocation dynamics: Barba Navaretti et al. (2004) have pointed out a compositional effect of international entry, i.e. if MNEs entering in a region are more productive than their local counterparts, the greater their share in the total composition of output in a given region, the higher the income level of a given region, and the steeper its growth path.

Not surprisingly, since aggregate income levels are ultimately driven by the sum of value-

\textsuperscript{3}In particular, the European Commission has proposed to allocate a total of 345 billion of euros in the period 2007-2013 to correct for regional disparities arising after the EU enlargement to the countries of Central and Eastern Europe.

\textsuperscript{4}The idea is that, if convergence is in place, as integration proceeds initial (per capita) income levels of regions should be negatively correlated (through the beta coefficient of a linear regression) to their average growth rates.

\textsuperscript{5}Exploiting new econometric techniques, which allow a correction of the standard dynamic panel GMM estimator for spatial correlation, Badinger et al. (2004) are however shedding further light on the available measures of convergence, finding a faster convergence rate than previously measured in a sample of EU regions.
added micro data, the previously discussed sources of regional disparities can be reconducted to
the channels that the I.O. literature has identified as driving changes in aggregate measures of
industry output: a within-plant component deriving from plant-level changes in productivity, a
between-plant component that reflects modifications in the allocation of inputs, and the effect
of entry and exit of firms. As it can be seen, although the macro and the I.O. approach differ in
terms of methodologies and scope of analysis, a remarkable parallelism seems to exist between the
channels they identify as sources of change: technological diffusion is in fact a key driver of firm-
level productivity changes, while phenomena of industrial restructuring are essentially induced
by a modification in the firms’ allocation of inputs. Furthermore, in line with the compositional
effect of MNEs identified at the macro level, also the I.O. approach has pointed out that TFP
changes are linked to the ownership of the firm, with foreign subsidiaries displaying in general
different productivity dynamics with respect to domestic firms (De Backer and Sleuwaegen,
2003).

Notwithstanding these similarities, nevertheless a key advantage of the I.O. approach is that
aggregate industry changes can be precisely measured through appropriate decompositions of
TFP indexes: some studies (Baily et al., 1992 on US data) find a prevalence of reallocation effects;
others (Van Biesebroeck, 2003 on Colombian data, or Levinsohn and Petrin, 2003 on Chilean
data) highlight the impact of within-plant productivity changes, while net entry effects are found
relevant by, e.g., De Loecker and Konings (2005) in their TFP decomposition performed on
Slovenian data.

Given the latter results, in the next section we will try to exploit the I.O. approach in order
to precisely measure the various components that affect the evolution of regional output.

3 Methodological framework

Let $\omega_{jt}$ denote the aggregate total factor productivity of a given industry $j$ at a point in time
$t$. The latter has been usually measured as the residual obtained subtracting the predicted log
output $\hat{y}_{jt}$ from the actual log output $y_{jt}$ of the considered $j$—industry. In particular, $\hat{y}_{jt}$ has
been in general calculated using log inputs $x_{jt}$ within a Cobb-Douglas aggregate production
technology characterized by a vector $\beta$ of coefficients. Hence

$$\omega_{jt} = y_{jt} - \hat{y}_{jt} = y_{jt} - \beta' x_{jt}$$

A shortfall of this methodology, however, is that it implies that any redistribution of inputs
across plants results in the same aggregate output, which might not be the case if, for example,
firms within the industry are heterogeneous in productivity levels and new inputs flow to the
most productive firms. Hence, the literature has started to employ firm-level\textsuperscript{6} TFP estimates of the form
\[
\omega_{ijt} = y_{ijt} - \hat{y}_{ijt} = y_{ijt} - \beta'x_{ijt}
\] (2)
where the sub-index denotes firm $i$. Industry-level TFP estimates are then obtained aggregating firm-level measure and constructing aggregate productivity indexes of the form $\Omega_{jt} = \sum_{i=1}^{N} s_{ijt} \omega_{ijt}$, where a measure $\Omega_{jt}$ of the industry-level TFP is obtained as a weighted average of the firm-specific productivity measure $\omega_{ijt}$, using output or input shares $s_{ijt}$ as weights\textsuperscript{7}.

As noted by Levinsohn and Petrin (2003), the aggregation $\Omega_{jt}$ implies two crucial shortfalls. First, due to the weights employed in the summation, no function of $\Omega$ can reproduce the dynamics of total output $y_{jt}$\textsuperscript{8}. Second, since $\Omega_{jt}$ is an index, with no clear unit of measurement, aggregation and comparisons across industries and over time are problematic. Because of these two shortfalls, the traditional methodology for the aggregation of firm level productivities is clearly not useful as a tool to explore the regional dynamics of output.

In order to solve these problems, it is however possible to exploit a methodology developed by Levinsohn and Petrin (2003), who have proposed to solve the aggregation problem of firm-specific TPF measures using predicted output levels as weights: in doing so, every element in the sum of aggregate productivity has as units the original unit in which $y_{it}$ is measured, and hence measurements across industries and over time become possible, as well as a reaggregation of different industries in order to reproduce aggregate regional output.

This can be easily seen reworking Equation (2) as
\[
Y_{jt} = \sum_{i=1}^{N} z_{ijt}TFP_{ijt}
\] (3)
where $Y_{jt}$ is the aggregate output (in levels) of our $j-$industry, $TFP_{ijt} = e^{\omega_{ijt}}$ and $z_{ijt} = e^{\beta'x_{ijt}}$.

Denoting $\Delta Y_{jt} = \sum_{i=1}^{N} z_{ijt}TFP_{ijt} - \sum_{i=1}^{N} z_{ijt-1}TFP_{ijt-1}$ and manipulating this expression in order to take into account also the reallocation effects induced by the entry and exit of firms,

\textsuperscript{6}Technically, you should use plant-level data, since different plants might have different productivity levels. In the remaining of the paper, we shall however assume that each firm identifies a single plant.

\textsuperscript{7}Baily et al. (1992) where among the firsts to calculate in this way the aggregate productivity index using as weights the output shares of each firm. Foster et al. (1998) however argue that, being output dependent from productivity, it is better to use input shares as weights, hence $s_{it} = X_{it}/\sum_j X_{jt}$, where $X_{it} = e^{x_{it}}$. Van Biesebroeck (2003) warns that using inputs as weights nevertheless induces a lower productivity average, as plants that improve productivity most are those that use less inputs per unit of output, and hence receive a low weight.

\textsuperscript{8}For example, the change in industry output while holding industry inputs constant cannot be recovered as the product of output at $t - 1$ times $\Delta \Omega$. Similar critiques to the aggregation $\Omega_{jt}$ are also pointed out by Van Biesebroeck (2003).
it is possible to decompose the changes in the aggregate output of the \( j \)-industry, \( \Delta Y_{jt} \), as

\[
\Delta Y_{jt} = \sum_{i \in C} \left[ z_{ijt-1} \Delta TFP_{ijt} + \Delta z_{ijt} TFP_{ijt-1} + \Delta z_{ijt} \Delta TFP_{ijt} \right] +
\]

\[
+ \sum_{i \in E} z_{ijt} TFP_{ijt} - \sum_{i \in X} z_{ijt-1} TFP_{ijt-1}
\]

where the total number of plants \( N \) has been decomposed in three sets: those who continue their business over time (\( C \)), those who enter at a given time (\( E \)) and those who exit (\( X \)). The first term in square brackets measures the changes to aggregate output induced by changes in productivity, holding the inputs constant, while the second term captures the reallocation effects of inputs; the third term is the covariance between the productivity growth and reallocation. The second and third addendum measure instead the effect of net entry on aggregate output growth.

With reference to the general findings of the literature, we can further decompose Equation (4) to incorporate the effects of ownership, distinguishing domestic from multinational plants. This can be simply done by distinguishing the inputs \( z_{it}^M \) and productivity \( TFP_{it}^M \) of multinational firms from the domestic ones, \( z_{it}^D \) and \( TFP_{it}^D \), with \( M \) and \( D \) denoting the multinational or domestic ownership of each firm, respectively. Hence, it is possible to rewrite Equation (4) as

\[
\Delta Y_{jt} = \sum_{H=M,D} \left\{ \sum_{i \in C} \left[ z_{ijt-1}^H \Delta TFP_{ijt}^H + \Delta z_{ijt}^H TFP_{ijt-1}^H + \Delta z_{ijt}^H \Delta TFP_{ijt}^H \right] +
\]

\[
+ \sum_{i \in E} z_{ijt}^H TFP_{ijt}^H - \sum_{i \in X} z_{ijt-1}^H TFP_{ijt-1}^H \right\}
\]

Equation (5) is very flexible, since essentially it decomposes the changes in aggregate output of industry \( j \) starting from firm-level data, thus allowing for firm heterogeneity. Moreover, since the decomposition uses absolute input values rather than shares as ‘weights’\(^9\), the same decomposition can be easily reaggregated across industries. Given a region \( r \) composed of \( M \) industries, the changes in the regional aggregate output \( \Delta Y_{rjt} \) can infact be easily obtained as

\[
\Delta Y_{rjt}^r = \sum_{j=1}^M \Delta Y_{jrt}
\]

Equations (5) and (6) provide a microfoundation of the changes in regional aggregate output through the underlying firm-level dynamics. As such, they allow us to explore the sources of regional disparities, distinguishing productivity changes from reallocation of inputs, the role of

\(^9\)Technically the \( z_{it} \) are not weights, since they do not sum to 1. As a result, some of the decompositions traditionally used by the literature (e.g. Haltiwanger, 1997; Griliches and Regev, 1995; Baldwin and Gu, 2003) cannot be applied here. We will come back to this when fitting this decomposition to our dataset.
multinational firms, the effects of changes in market structures (entry and exit of firms), and
the specific contributions of each industry dynamics.

4 A decomposition of regional aggregate output

In this section we present the result of our decomposition applied to the case of Romania, a
large transition country displaying interesting dynamics across the eight regions in which the
Eurostat NUTS2 classification divides its territory. In particular, Table 1 shows the per capita
GDP (in PPS) of the Romanian regions as a percentage of the national average from 1995 to
2001. As it can be seen, regions are diverging, with the standard deviation of their income (a
measure known as $\sigma$—convergence) more than doubling in the considered period. In particular,
only three regions (Vest, Centru and Bucuresti) display income dynamics in line or above the
national average, with the capital region, Bucuresti, clearly outperforming all the others\(^{10}\).

In order to microfound the sources of these increasing disparities, we employ a dataset
composed of domestic firms and affiliates of multinational enterprises (MNEs) operating for
the period 1995-2001 in Romania, as retrieved from the AMADEUS database\(^{11}\). In particular,
we have obtained information on the location of each firm within each of the eight Romanian
regions, the industry in which these firms operate (at the NACE-4 level), as well as yearly
balance sheet data for the period 1995-2001 on tangible and intangible fixed assets, total assets,
number of employees, material costs, sales, added value and ROA/Ebit. Due to the stratified
nature of the dataset, with firms added every year, we can recover information on firms always
operating in the considered time span, on firms who entered between 1995 and 2001 (since we
have information on the year of incorporation of each firm), and on exiting firms (i.e. those
firms still present in the dataset which do not report any more information after a given year)\(^{12}\).
In particular, we observe entry over time for some 25 per cent of domestic firms and around 50
per cent of MNEs, yielding 7,860 domestic firms and 3,285 MNEs in year 2001. In terms of exit
rates [riportare di quante imprese osserviamo exit come definita venerdì, i.e. senza
considerare missing obs; rifare le Tabelle considerando exit solo come ci siamo detti]

In order to validate of our data, we have calculated the correlation between measures of
\footnote{The case of Romanian regions is in line with the dynamics experienced by other countries in the area. The
in the Countries of Central and Eastern Europe has been disproportionately concentrated in a few regions,
particularly in capital cities and surrounding areas.}
\footnote{The AMADEUS database is provided by Bureau van Dijck, a consulting firm operating in Brussels; it contains
balance sheet data in time series of a sample of roughly 5,000,000 companies operating in various European
countries.}
\footnote{Clearly, it could be the case that a firm has exited from the dataset, but not from the market. As a result,
a robustness check of our treatment of exiting firms is provided in Annex 2. In any case, although the overall
output decomposition does not seem to be biased by this issue, given the nature of our data all considerations on
the specific contribution of net entry have to be taken with some caution.}
yearly aggregate output levels and growth rates, using both the sum of firm-specific deflated sales contained in our dataset as a proxy of real output\textsuperscript{13} and the figure of real output retrieved from official sources (Eurostat and WIIW). The correlations are above 0.7 and significant, thus implying that our firm-level data, when appropriately aggregated, are able to reproduce the actual evolution of regional output in Romania.

To calculate firm-specific productivity estimates, we have first assigned our firms to 27 different NACE2 industries, reported in Table 2 together with the firms’ regional distribution, and then we have applied the Levinsohn and Petrin (2003a) methodology to each industry\textsuperscript{14}. This has allowed us to solve the simultaneity bias affecting standard estimates of firm-level productivity, as well as to derive TFP estimates from heterogeneous, industry-specific production functions (see Annex 1 for further details)\textsuperscript{15}. Furthermore, we have calculated different TFP estimates for domestic and multinational firms, in line with the findings of De Backer and Sleuwaegen (2003). In order to check the appropriateness of our correction for simultaneity, Table 3 reports, for a sample of domestic firms, the clear bias that emerges when confronting the results of the semi-parametric estimates of productivity with standard OLS results. Similar results can be obtained when confronting productivity estimates relative to MNEs data.

The only caveat of our approach is related to the fact that firm-specific measures of $z$ and \textit{TFP} in Equation (6) acquire not only an industry, but also a region-specific dimension. Nevertheless, in our analysis they are estimated using $\beta$ coefficients which are only industry-specific, due to the insufficient number of observations available for each industry/region pair. While it seems safe to assume input elasticities to be industry- rather than region-specific, however the bottom part of Table 3 reports the semi-parametric estimates of productivity calculated using regional fixed-effects. \([\text{xi: levpet ... i.nutsii; se non è possibile, allora } "\text{calculated for those industry/region pair in which the number of firms was high enough to allow for enough variation in the data"}].\] As it can be seen, the regional dimension does not seem to affect the validity of our reported $\beta$ coefficients, which can thus be considered only in their inter-industry variation.

\textsuperscript{13}We have deflated our balance sheet data using a total of 49 NACE2 or NACE3 industry-specific price indices retrieved from the Eurostat New Cronos database, according to data availability. We have then used deflated sales as a proxy for output, given the better quality of these time series with respect to the ones reporting value added.

\textsuperscript{14}Industry-specific TFP estimates have been calculated on firm-level data for the 1995-2001 period, thus ensuring an adequate number of observations for each productivity estimate. In a few cases (i.e. NACE16, 20 and 65) industries have displayed insufficient variation to identify the input coefficients. Accordingly, these industries have been eliminated altogether in all the reported Tables.

\textsuperscript{15}Using ordinary least squares when estimating productivity implies treating labor and other inputs as exogenous variables. However, as pointed out by Griliches and Mareiss (1995), profit-maximizing firms immediately adjust their inputs (in particular capital) each time they observe a productivity shock, which makes input levels correlated with the same shocks. Since productivity shocks are unobserved to the econometrician, they enter in the error term of the regression. Hence, inputs turn out to be correlated with the error term of the regression, and thus OLS estimates of production functions are biased. Olley and Pakes (1996) and Levinsohn and Petrin (2003a) have developed two similar semi-parametric estimation procedures to overcome this problem.
In Table 4 we exploit the productivity estimates so obtained for calculating the decomposition of changes in aggregate output $\Delta Y_t$, according to Equations (5) and (6). To provide a synthetic overview of our exercise, we report for each region and for the whole country the changes in output attributable to each component of Equation (5) as period averages for the years 1995-2001. As already recalled, such a decomposition has the advantage that every element in the sum has as units the original unit in which $y_{it}$ is measured, and hence comparisons and aggregation across industries/regions and over time become possible.

The second column of Table 4 reports the average change in regional output $\Delta Y_t$ (measured in '000s of real euros) as calculated from the aggregation of all firm-level observations in our dataset: the same figure can be obtained as the sum, for all sample firms, of the five elements in which we have decomposed the regional output ("all firms" headings), thus deriving important information on the sources of its dynamics. As it can be seen, the aggregate changes in regional output $\Delta Y_t$ are on average negative for the considered period, consistently with the transition experience of Romania. However, in line with the dynamics of output typical of transition countries, which in general tend to display a U-shaped evolution over time, in our sample we observe that the yearly growth rates of Romanian regions tend to increase in the last years of the considered period, as confirmed by the previously discussed correlation of our figures with official output data (see also Table 5).

Among the various components driving the aggregate dynamics of output, confronting columns 5 and 8 in Table 4 it can be seen that, on average for all firms, the effects induced by changes in productivity $(z_{it-1} \Delta TFP_{it})$ tend to be positive across regions in Romania, but their effect is largely overcome by the negative contribution to output deriving from the reallocation of inputs $(\Delta z_{it} TFP_{it-1})$. Net entry tends instead to positively contribute to the dynamics of output [riporta solo una colonna Net Entry = Entry-Exit]. All the latter results are consistent with the early phases of a transition country. In fact, given the general finding that firms in CEEs under the planned regime suffered from labour hoarding, there is ample evidence in the literature showing that industries in transition countries tend to destroy jobs, and thus decrease output, as far as existing firms are concerned, while a substantial positive contribution in terms of job creation and growth comes from the net entry of new firms\(^{16}\).

As a further control for the consistency of our general results, we present in Table 5 the yearly decomposition of regional output changes for the three regions (Vest, Centru and Bucuresti) that, on the basis of official data, are reported to outperform the others. According to our decomposition, in these three regions the negative overall impact of the reallocation component

\[^{16}\text{In particular, using TFP measures De Loecker and Konings (2005) are able to link the positive productivity growth observed in Slovenia (another transition country) to the observed rates of job creation and destruction, arguing that firms have engaged in cost cutting strategies, which may include a more efficient use of labor, innovation, but also the replacement of bad jobs by good ones.}\]
(ΔzitTFPit−1), reported in column 8, tends to decrease in the last years of the sample period, thus inducing a positive stimulus to aggregate output changes. This is perfectly consistent with the findings of Table 1, derived from official data.

Through the analysis of our decomposition, we can therefore derive a first general result: by and large, the increase of regional disparities in Romania is associated to cross-regional differences in the U-shaped pattern of output evolution. All the Romanian regions in the early years of transition experienced negative output changes, (mainly) induced by a reallocation of factors of production, with this process ending quicker in some regions with respect to others. As a result, while the aggregate output starts to increase, regional disparities open up.

5 What drives regional disparities?

The most important feature of the decomposition proposed in Tables 4 and 5, however, is the availability of information related to the different contributions provided by domestic and multinational firms to the evolution of aggregate regional output. In particular, over the considered period the MNEs’ affiliates display in all regions, as expected, a positive contribution to aggregate output via the channel of productivity changes (zit−1ΔTFPit), which is larger than the negative productivity changes experienced by domestic firms, thus inducing an overall positive effect of productivity on output at the national level (Table 4, columns 3 vs. 4). However, this positive contribution of MNEs’ affiliates is more than compensated by the higher (negative) reallocation effects (ΔzitTFPit−1) that MNEs, on average, have displayed in all the Romanian regions with respect to domestic firms (Table 4, columns 6 vs. 7). The latter finding is not surprising, since it is known in the transition literature that the increased competitive pressure that emerges from the international market may push firms to engage in more restructuring (Konings et al., 2005).

For the case of the three best-performing regions, however, the negative reallocation effect induced by MNEs, while larger than the one generated by domestic firms at the beginning of our sample period, tends instead to become smaller over time (Table 5, columns 6 vs. 7). In the last year, 2001, MNEs generate even a positive reallocation effect on total output changes, with inputs thus either reallocated towards the most productive firms or substantially increased. Furthermore, entering MNEs in these three regions positively affect output changes, with effects

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17 In all our results, however, the performance of the capital region, București, is under estimated. This is due to the fact that most of the growth in the capital regions of transition countries derives from the services sector (EC, 2004), a sector which is under represented in our dataset, since Amadeus tracks medium to large firms (firms whose total turnover or assets of at least $12 million, or total employment of at least 150), while firms in the services sector tend to be smaller.

18 Clearly, in the case of MNEs this explanation is more likely to hold for the acquisition of domestic firms or joint ventures, rather than for greenfield investments, although we cannot exclude some input reallocation as transition progresses even in the latter case.
growing larger over time and unmatched by similar dynamics from domestic firms (Table 5, last six columns).

Hence, a second general result can be inferred from our analysis: on average, foreign direct investments rather than domestic firms are instrumental in inducing regional growth, thanks to their higher and positive productivity changes, deeper restructuring and faster net entry contributions. However, these positive contributions come at the detriment of widening regional disparities, since the effects of MNEs, while more or less homogeneous across regions, tend to have different orders of magnitude, with some regions currently benefitting more than others.

To explore where these dynamics lead in the long run, i.e. what happens to regional disparities once controlling for the compositional effect on regional output induced by the presence of MNEs, it is important to look at the behaviour of domestic firms. As we have already seen, the latter firms, apart from a negative reallocation term, which is not surprising, display also negative productivity changes, which, if structural, might significantly hamper the future ability of regions to reduce disparities. Among the various possible reasons for this phenomenon, particularly worrisome is the eventual existence of a link between the presence of MNEs and the negative productivity performance of domestic firms. In fact, given the positive compositional effects of MNEs on regional growth, regions will ex-ante compete to attract foreign investment, but in so doing, due to the possible negative spillovers to domestic firms, ceteris paribus their speed of convergence might be structurally reduced, and thus regional disparities might tend to persist. Because of this reason, the issue is receiving widespread attention by economists and policy makers.

In particular, the literature has identified several channels through which MNEs might affect domestic firms’ productivity, but none of these has a priori a positive or a negative sign. The presence of MNEs in the same industry could in fact compress market shares and thus crowd-out domestic firms, but it could also generate positive spillovers thanks to a learning process from the superior technology with which MNEs are in general endowed. Analogously, the presence of MNEs in industries which are upward or downward in the production chain of the considered domestic firm might have a positive or a negative effect, according to the changes in the market structure induced by the entry of the multinationals19.

Limiting our attention to the empirical evidence available for transition countries, Damijan et al. (2001), Djankov and Hoekman (2000) and Konings (2001) find mixed evidence of spillovers from the presence of multinationals on domestic firms in the same industry. More recently, Smarzynska Javorcik (2004), instead, working on Lithuanian regional data and exploiting a measure of firm level productivity which, as in our case, controls for the simultaneity bias in firms’decisions, has detected significant positive spillovers arising through backward linkages, i.e.

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19 In their survey, Gorg and Greenaway (2002) discuss the inconclusive evidence emerging from several empirical contributions on the issue.
generated through contacts between multinational affiliates and local input suppliers. She finds instead no clear evidence in favour of neither intra-industry spillovers, nor forward linkages.

In order to shed further light on this issue, we have performed an econometric exercise relating the productivity of domestic firms to the presence of MNEs affiliates. Following the latter approach, the baseline specification of our econometric model is as follows:

$$\Delta TFP_{ijrt} = \alpha_0 + \alpha_1 HP_{jr(t-1)} + \alpha_2 BP_{jr(t-1)} + \alpha_3 FP_{jr(t-1)} + \alpha_4 HERF_{j(t-1)} + \alpha_5 yinc_i + \alpha_t + \alpha_r + \alpha_j$$  \hspace{1cm} (7)

where \(i\) denotes the domestic firm, \(j\) the industry and \(r\) the region at year \(t\), on the basis of the classification of our dataset. The dependent variable \(\Delta TFP_{ijrt}\) is the change (in levels) of the total factor productivity undergone by firm \(i\), in sector \(j\) and region \(r\), from year \((t - 1)\) to year \(t\), calculated according to the Levinsohn and Petrin (2003a) methodology previously discussed, and used for our decomposition of output.

To assess whether MNEs negatively affect domestic firms, the change in the domestic firms’ productivity is regressed against three foreign penetration indexes, \(HP_{jr(t-1)}\), \(BP_{jr(t-1)}\) and \(FP_{jr(t-1)}\) all lagged one-period, in order to control as well for a possible endogeneity bias [control for lags higher than one]. In particular, \(HP_{jr(t-1)}\) is an index of horizontal penetration, capturing the intra-industry presence of MNEs and calculated as the ratio of multinational employees over of the total ones in the considered industry \(j\), region \(r\) and year \(t\). The index \(BP_{jr(t-1)}\) measures the backward penetration, i.e. the foreign presence in industries from which industry \(j\)’s domestic firms are sourcing their inputs. It is computed as the weighted sum of the horizontal penetration figures of all the suppliers’ industries, according to the formula \(BP_{jr(t-1)} = \sum_k \alpha_{jk} HP_{krt}\), where \(\alpha_{jk}\) is the proportion of industry \(j\)’s total inputs sourced from industry \(k\), an information retrieved from a proper reaggregation of the 1998 Romanian Input Output Matrix\(^{20}\). This index increases for higher values of horizontal penetration in the supplying sectors, though this impact is driven by the weights, which are intended to capture the relative intensity of interactions among the different industries. Analogously, the index \(FP_{jr(t-1)}\) measures the forward penetration, i.e. the presence of multinationals’ affiliates in industries which are sourcing inputs from sector \(j\). Speculatively to the BP index, it is defined as \(FP_{jr(t-1)} = \sum_m \beta_{jm} HP_{mrt}\), where \(\beta_{jm}\) is the proportion of output sold from industry \(j\) to \(k\), out of industry \(j\)’s total inputs sales. The same interpretation of the previous index applies. Clearly, in the calculation of both the BP and FP indexes, in order to avoid a double counting of the foreign presence we have always excluded from the computation the inputs supplied and sourced within the same industry, since any potential intra-industry effect is already taken into account by the HP index.

\(^{20}\)We are grateful to Beata Smarzynska Javorcik for having provided us with this Table.
To control for the market structure that might affect the domestic firms’ productivity, we have calculated, using the market shares of all the sample’s firms for each industry $j$, the Herfindahl Index, $HERF_j(t-1)$, which enters in the regression with its lagged value [control for changes in Herf or medianempl]. We proxy the age of each firm in the sample via its date of incorporation, $yinc$ (i.e. younger firms have a higher year of incorporation), which allows us to test for eventual structural differences in the productivity performance of different cohorts of entrants. Finally, $\alpha_t$, $\alpha_r$, and $\alpha_j$ are time, region and industry specific dummies, respectively.

The specification reported in Equation (7) allows us to control for several potential econometric problems. First of all, one has to control for unobserved firm, time, region and industry-specific characteristics that might affect the correlation between firm productivity and foreign presence. The inclusion of time, industry and regional fixed effects controls for these unobservables, while firm-specific heterogeneity is captured by the variable measuring the year of incorporation of each firm\textsuperscript{21}. Another typical econometric concern of this kind of estimates, i.e. the simultaneity bias in the measure of firm-level productivity, is addressed using the already discussed Levinsohn and Petrin (2003a) methodology to calculate firm-level productivity estimates. Finally, since we perform a regression on micro units using mainly aggregated variables as covariates (at the regional-industry level) we control for the potential downward bias in the estimated errors by clustering the standard errors for all firm-level observations belonging to the same region-industry pair.

The results of the regression are presented in Table 6. The presence of multinationals in the same industry of domestic firms positively affects their changes in productivity, thus indicating the presence of some spillover effects. Positive effects are also detected when considering the case of MNEs sourcing their products from domestic firms (forward penetration). On the contrary, when MNEs operate in industries from which domestic firms source their inputs (backward penetration), they negatively affect domestic firms’ productivity levels. Finally, the degree of concentration of the industry does not seem to affect domestic firms’ productivity changes.

The above results are again consistent with the picture of a transition economy, in which the fixed ties between domestic firms deriving from the planned system are disrupted and replaced by market relations. The existence of positive and significant backward linkages from MNEs to domestic firms is in fact in line with the findings of Smarzynska Javorcic (2004), while the negative consequences accruing to domestic firms from the presence of MNEs in the upstream sector, are consistent with the disruption of historic linkages replaced by market relations with

\textsuperscript{21}Contrary to standard practice, we have opted not to time-diiference the covariates related to the MNEs’ presence. In so doing, in fact, we would have radically eliminated an eventual unobserved variable bias, but at the cost of imposing the assumption that changes in productivity of domestic firms are driven only by changes in the presence of MNEs, which is not necessarily true, since domestic firms might be affected differently by the same stock of MNEs over time, e.g. due to a learning process.
concentrated suppliers. However, provided that adequate levels of competition are maintained, these effects are likely to disappear as soon as the restructuring of the various industries, and the redefinition of the economic linkages across firms, is over. Relatively new to the literature is instead the robustness with which the presence of intra-industry positive spillovers from MNEs to domestic firms emerges in our estimates.

Putting things together, a third general conclusion can be inferred from our analysis: eventual negative effects from the presence of MNEs on the productivity of domestic firms are essentially related to the dynamics of transition, while we have some evidence of structural positive spillovers likely to last in the long run.

As a result, regional disparities deriving from the presence of foreign investment tend to have a short term nature. [Domestic firms badly performing $\Rightarrow$ SOEs?? SBC?]

6 Conclusions

In this paper we have exploited a methodology able to solve the aggregation problem of firm-specific TFP measures using predicted output levels as weights and controlling for the simultaneity bias in the estimates of these measures. The methodology allows us to correctly decompose output across industries, time and classes of firms (domestic vs. MNEs), thus providing us with a micro-foundation of the sources of regional disparities.

In particular, applying our methodology to the case of Romania, a transition economy characterized by increasing regional disparities, the paper shows that, by and large, the increase of regional disparities in the country is associated to cross-regional differences in the U-shaped pattern of output evolution. All the Romanian regions in the early years of transition experienced in fact negative output changes, (mainly) induced by a reallocation of factors of production, with this process ending quicker in some regions with respect to others. As a result, while the aggregate output starts to increase, regional disparities start to open up.

Foreign investment play a key role in this process: from one side, MNEs affiliates are shown to generate higher and positive productivity changes and larger net entry contributions to regional output with respect to domestic firms; however, they also induce deeper restructuring processes, negatively affecting the same regional output. The latter effect however varies across regions, with some regions quicker in recovering growth through input reallocation. As a result, the relationship between foreign investment and the emergence of regional disparities does not seem to have a structural nature, being it linked to the different orders of magnitude with which MNEs affect output growth across regions and to the ongoing process of economic transition experienced by Romanias.

Finally, the econometric exercise has revealed that MNEs seem also to generate positive effects for the productivity of domestic firms, thus allowing for another channel through which
they contribute to regional output growth (i.e. via intra-industry spillovers and backward linkages). Nevertheless, the presence of MNEs in industries which source intermediates to domestic firms tends to be negatively associated with their productivity performance. However the latter effect, again, is likely to have a short term nature, and should disappear as soon as the restructuring of the various industries and the redefinition of the economic linkages across firms is over, provided that adequate levels of competition are maintained in all industries.
References


Annex 1: Levinsohn and Petrin (2003a) productivity estimates

Let \( y_t \) denote (the log of) a firm’s output in a Cobb-Douglas production function of the form

\[
y_t = \beta_0 + \beta_1 l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t
\]

(A1.1)

where \( l_t \) and \( m_t \) denote the (freely available) labour and intermediates inputs in logs, respectively, and \( k_t \) is the logarithm of the state variable capital. The error term has two components: \( \eta_t \), which is uncorrelated with input choices, and \( \omega_t \), a productivity shock unobserved to the econometrician, but observed by the firm. Since the firm adapts its input choice as soon as she observes \( \omega_t \), inputs turn out to be correlated with the error term of the regression, and thus OLS estimates of production functions yield inconsistent results.

To correct for this problem, Levinsohn and Petrin (2003a), from now on LP, assume the demand for intermediate inputs \( m_t \) (e.g. material costs) to depend on the firm’s capital \( k_t \) and productivity \( \omega_t \), and show that the same demand is monotonically increasing in \( \omega_t \). Thus, it is possible for them to write \( \omega_t \) as \( \omega_t = \omega_t(k_t, m_t) \), expressing the unobserved productivity shock \( \omega_t \) as a function of two observables, \( k_t \) and \( m_t \).

To allow for identification of \( \omega_t \), LP follow Olley and Pakes (1996) and assume \( \omega_t \) to follow a Markov process of the form \( \omega_t = E[\omega_t|\omega_{t-1}] + \xi_t \), where \( \xi_t \) is a change in productivity uncorrelated with \( k_t \). Through these assumptions it is then possible to rewrite Equation (A1.1) as

\[
y_t = \beta_1 l_t + \phi(k_t, m_t) + \eta_t
\]

(A1.3)

where \( \phi(k_t, m_t) = \beta_1 + \beta_k k_t + \beta_m m_t + \omega_t(k_t, m_t) \). By substituting a third-order polynomial approximation in \( k_t \) and \( m_t \) in place of \( \phi(k_t, m_t) \), LP show that it is possible to consistently estimate the parameter \( \hat{\beta}_1 \) and \( \hat{\phi}_t \) in Equation A1.3. For any candidate value \( \beta^*_k \) and \( \beta^*_m \) one can then compute a prediction for \( \omega_t \) for all periods \( t \), since \( \hat{\omega}_t = \hat{\phi}_t - \beta^*_k k_t - \beta^*_m m_t \) and hence, using these predicted values, estimate \( E[\omega_t|\omega_{t-1}] \). It then follows that the residual generated by \( \beta^*_k \) and \( \beta^*_m \) with respect to \( y_t \) can be written as

\[
\eta_t + \xi_t = y_t - \hat{\beta}_1 l_t - \hat{\beta}_k k_t - \hat{\beta}_m m_t - E[\omega_t|\omega_{t-1}]
\]

(A1.4)

Equation (A1.4) can then be used to identify \( \beta^*_k \) and \( \beta^*_m \) using the following two instruments: if the capital stock \( k_t \) is determined by the previous period’s investment decisions, it then does not respond to shocks to productivity at time \( t \), and hence \( E[\eta_t|\omega_{t-1}] = 0 \); also, if the last period’s level of intermediate inputs \( m_t \) is uncorrelated with the error period at time \( t \) (which is plausible, e.g. in the case of material costs), then \( E[\eta_t|\omega_{t-1}, m_{t-1}] = 0 \).

Through these two moment conditions, it is then possible to write a consistent and unbiased estimator for \( \beta^*_k \) and \( \beta^*_m \) simply by solving

\[
\min_{(\beta^*_k, \beta^*_m)} \sum_h \sum_t (\eta_t + \xi_t) Z_{ht}
\]

(A1.5)

with \( Z_t \equiv (k_t, m_{t-1}) \) and \( h \) indexing the elements of \( Z_t \).
Annex 2: Controlling for exiting firms

Lacking specific information on firms’ exit, in the paper we have considered as exiting firms those firms whose data are not reported anymore after a given year. We present here a robustness check of this assumption, which we believe is useful as a general correction of what constitutes the major drawback of the Amadeus dataset.

Employing a standard aggregate productivity index of the form \( \Omega_t = \sum_{i=1}^{N} s_{it} \omega_{it} \), where the aggregate productivity \( \Omega_t \) is measured as the weighted average of the firm-specific productivity measure \( \omega_{it} \), using input shares \( s_{it} \) as weights, Haltiwanger (1997) introduces a decomposition of changes in this measure as

\[
\Delta \Omega_t = \sum_{i \in C} [s_{it-1} \Delta \omega_{it} + \Delta s_{it} (\omega_{it-1} - \Omega_{t-1}) + \Delta s_{it} \Delta \omega_{it}] + \sum_{i \in E} s_{it} (\omega_{it} - \Omega_{t-1}) - \sum_{i \in X} s_{it-1} (\omega_{it-1} - \Omega_{t-1})
\]

(A2.1)

where again the total number of plants \( N \) has been decomposed in three sets: those who continue their business over time \( (C) \), those who enter at a given time \( (E) \) and those who exit \( (X) \). Essentially, in this decomposition the reallocation and net entry components involve a comparison with the productivity of an average firm. Continuing firms are said to contribute positively to aggregate productivity if they are more productive than an average firm in the base year. Entering firms contribute positively if their productivity in the end year exceeds that of an average firm in the base year. For exiting firms, the contribution is said to be positive if they are less productive than an average firm in the base year.

Working on the latter decomposition, Baldwin and Gu (2002) argue that, since entering firms essentially replace exiting firms, in order to properly account for the contribution of firm turnover it is more appropriate to compare productivity between entering and exiting firms. Hence, they replace the term \( \Omega \) in Equation (A2.1) with the weighted average productivity of exiters, denoted as \( \Omega^X \). As a result, the last term of Equation (A2.1) disappears, yielding

\[
\Delta \Omega_t = \sum_{i \in C} [s_{it-1} \Delta \omega_{it} + \Delta s_{it} (\omega_{it-1} - \Omega^X_{t-1}) + \Delta s_{it} \Delta \omega_{it}] + \sum_{i \in E} s_{it} (\omega_{it} - \Omega^X_{t-1})
\]

(A2.2)

Now, given the selection bias of the Amadeus dataset, which essentially records "surviving" firms, a good proxy of \( \Omega^X \) can be derived as \( \min[\omega^N, \omega^E] - \varepsilon \), with \( \varepsilon \to 0 \), i.e. a firm will tend to exit when she will have an individual productivity level smaller than the minimum one displayed by the surviving firms in the dataset. As a result, a robustness check can be derived by comparing \( \Delta \Omega_t \) calculated as from Equation (A2.2) through the use of the previously introduced proxy, with an any other alternative decomposition of productivity (e.g. Equation A2.1), where one considers instead as exiters those firms whose data are not reported anymore in the dataset. The latter comparison applied to our sample did not display significant differences in the dynamics of productivity. We recall however that in our paper we do not concentrate on the dynamics of productivity \( \Delta \Omega_t \), but rather on the actual dynamics of output \( \Delta Y_t \). As a result, the two decompositions presented here cannot be directly linked to Equation (4) discussed in the paper.
Table 1. Regional disparities in Romania, 1995-2001.
(regional per capita GDP in PPS, as a percentage of the national average)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>RO01 Nord-Est</td>
<td>0.78</td>
<td>0.79</td>
<td>0.76</td>
<td>0.90</td>
<td>0.97</td>
<td>0.67</td>
<td>0.69</td>
</tr>
<tr>
<td>RO02 Sud-Est</td>
<td>0.96</td>
<td>0.99</td>
<td>0.99</td>
<td>0.90</td>
<td>0.86</td>
<td>0.85</td>
<td>0.82</td>
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<td>RO03 Sud</td>
<td>0.93</td>
<td>0.90</td>
<td>0.88</td>
<td>0.81</td>
<td>0.78</td>
<td>0.79</td>
<td>0.76</td>
</tr>
<tr>
<td>RO04 Sud-Vest</td>
<td>0.94</td>
<td>0.88</td>
<td>0.92</td>
<td>0.87</td>
<td>0.85</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>RO05 Vest</td>
<td>1.06</td>
<td>1.04</td>
<td>1.10</td>
<td>1.08</td>
<td>1.07</td>
<td>0.99</td>
<td>1.02</td>
</tr>
<tr>
<td>RO06 Nord-Vest</td>
<td>0.92</td>
<td>0.91</td>
<td>0.90</td>
<td>0.88</td>
<td>0.87</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>RO07 Centru</td>
<td>1.05</td>
<td>1.10</td>
<td>1.09</td>
<td>1.02</td>
<td>0.99</td>
<td>1.02</td>
<td>1.00</td>
</tr>
<tr>
<td>RO08 Bucuresti</td>
<td>1.34</td>
<td>1.38</td>
<td>1.37</td>
<td>1.54</td>
<td>1.61</td>
<td>1.98</td>
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<tr>
<td>σ-convergence</td>
<td>0.16</td>
<td>0.18</td>
<td>0.19</td>
<td>0.23</td>
<td>0.26</td>
<td>0.41</td>
<td>0.43</td>
</tr>
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</table>

Source: authors’ elaboration on Eurostat data (REGIO dataset).
σ-convergence is measured as the standard deviation of the regional indexes.
Table 2. Industry and regional distribution of sample firms, 2001

<table>
<thead>
<tr>
<th>NACE 2 Sector</th>
<th>Domestic</th>
<th>MNEs</th>
<th>Total sample</th>
</tr>
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<tbody>
<tr>
<td>10-14</td>
<td>245</td>
<td>72</td>
<td>317</td>
</tr>
<tr>
<td>15</td>
<td>1335</td>
<td>433</td>
<td>1768</td>
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<td>17</td>
<td>301</td>
<td>174</td>
<td>475</td>
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<td>18</td>
<td>592</td>
<td>350</td>
<td>942</td>
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<tr>
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<td>197</td>
<td>171</td>
<td>368</td>
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<td>100</td>
<td>42</td>
<td>142</td>
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<tr>
<td>22</td>
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<td>523</td>
</tr>
<tr>
<td>24</td>
<td>214</td>
<td>100</td>
<td>314</td>
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<td>243</td>
<td>146</td>
<td>389</td>
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<tr>
<td>26</td>
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<td>89</td>
<td>280</td>
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<td>43</td>
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<td>550</td>
<td>180</td>
<td>730</td>
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<td>29</td>
<td>151</td>
<td>86</td>
<td>237</td>
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<td>85</td>
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<td>1742</td>
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<td>2317</td>
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<tr>
<td>55</td>
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<td>46</td>
</tr>
<tr>
<td>92</td>
<td>96</td>
<td>50</td>
<td>146</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>NUTS2 Region</th>
<th>Domestic</th>
<th>MNEs</th>
<th>Total sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>RO01 Nord-Est</td>
<td>1107</td>
<td>349</td>
<td>1456</td>
</tr>
<tr>
<td>RO02 Sud-Est</td>
<td>816</td>
<td>283</td>
<td>1099</td>
</tr>
<tr>
<td>RO03 Sud</td>
<td>897</td>
<td>313</td>
<td>1210</td>
</tr>
<tr>
<td>RO04 Sud-Vest</td>
<td>566</td>
<td>213</td>
<td>779</td>
</tr>
<tr>
<td>RO05 Vest</td>
<td>694</td>
<td>422</td>
<td>1116</td>
</tr>
<tr>
<td>RO06 Nord-Vest</td>
<td>1293</td>
<td>460</td>
<td>1753</td>
</tr>
<tr>
<td>RO07 Centru</td>
<td>1275</td>
<td>496</td>
<td>1771</td>
</tr>
<tr>
<td>RO08 Bucuresti</td>
<td>1212</td>
<td>749</td>
<td>1961</td>
</tr>
</tbody>
</table>

Total sample  7860  3285  11145

Source: author’s elaboration from Amadeus data.
Table 3. A comparison of productivity estimates in a sample of domestic firms

<table>
<thead>
<tr>
<th>NACE</th>
<th>(15)</th>
<th>(17)</th>
<th>(22)</th>
<th>(24)</th>
<th>(34)</th>
<th>(36)</th>
<th>(64)</th>
<th>(73)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln (labor)</td>
<td>0.0257***</td>
<td>0.2391***</td>
<td>0.1708***</td>
<td>0.0429***</td>
<td>0.0552***</td>
<td>0.0874***</td>
<td>0.2124***</td>
<td>0.3757***</td>
</tr>
<tr>
<td>ln (materials)</td>
<td>0.8436***</td>
<td>0.9395</td>
<td>0.3115***</td>
<td>0.99***</td>
<td>0.9756***</td>
<td>0.7376***</td>
<td>0.8772***</td>
<td>0.399**</td>
</tr>
<tr>
<td>ln (capital)</td>
<td>0.0858***</td>
<td>0.0437***</td>
<td>0.3157*</td>
<td>0.0472</td>
<td>0.1617***</td>
<td>0.1264***</td>
<td>0.0048</td>
<td>0.0997*</td>
</tr>
<tr>
<td>OLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln (labor)</td>
<td>0.033***</td>
<td>0.2584***</td>
<td>0.1557***</td>
<td>0.0443***</td>
<td>0.0447***</td>
<td>0.0677***</td>
<td>0.2018***</td>
<td>0.3778***</td>
</tr>
<tr>
<td>ln (materials)</td>
<td>0.8608***</td>
<td>0.5869***</td>
<td>0.6516***</td>
<td>0.8517***</td>
<td>0.778***</td>
<td>0.8113***</td>
<td>0.6351***</td>
<td>0.4557***</td>
</tr>
<tr>
<td>ln (capital)</td>
<td>0.0684***</td>
<td>0.119***</td>
<td>0.1597***</td>
<td>0.0809***</td>
<td>0.1249***</td>
<td>0.0100***</td>
<td>0.2225***</td>
<td>0.1559***</td>
</tr>
<tr>
<td>OLS bias in labor coeff.</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>OLS bias in material coeff.</td>
<td>+</td>
<td>not sign.</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>OLS bias in capital coeff.</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>not sign.</td>
<td>-</td>
<td>-</td>
<td>not sign.</td>
<td>+</td>
</tr>
<tr>
<td>N. of obs.</td>
<td>6880</td>
<td>1608</td>
<td>1880</td>
<td>1132</td>
<td>360</td>
<td>2202</td>
<td>721</td>
<td>181</td>
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Table 4. The decomposition of regional output - 1995-2001 average changes in ‘000 of real €, all regions

<table>
<thead>
<tr>
<th>Region</th>
<th>ΔY_t</th>
<th>Productivity (z_{t-1} * ∆TFP_t)</th>
<th>Reallocation (TFP_{t-1} * ∆z_t)</th>
<th>Covariance (∆TFP_t * ∆z_t)</th>
<th>Entry</th>
<th>Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Firms</td>
<td>Dom</td>
<td>MNEs</td>
<td>All Firms</td>
<td>Dom</td>
<td>MNEs</td>
</tr>
<tr>
<td>RO01</td>
<td>-57081</td>
<td>-1373</td>
<td>1062</td>
<td>-312</td>
<td>-27328</td>
<td>-29319</td>
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<tr>
<td>RO02</td>
<td>-56284</td>
<td>-1671</td>
<td>2914</td>
<td>1243</td>
<td>-22281</td>
<td>-33860</td>
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<tr>
<td>RO03</td>
<td>-66153</td>
<td>-281</td>
<td>2801</td>
<td>2520</td>
<td>-32616</td>
<td>-33203</td>
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<td>RO04</td>
<td>-33774</td>
<td>-1247</td>
<td>1834</td>
<td>586</td>
<td>-14945</td>
<td>-19648</td>
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<tr>
<td>RO05</td>
<td>-30635</td>
<td>-1018</td>
<td>2657</td>
<td>1639</td>
<td>-12888</td>
<td>-18239</td>
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<td>RO06</td>
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<td>-2190</td>
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<td>3720</td>
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<td>-33866</td>
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<td>RO07</td>
<td>-91250</td>
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<td>1056</td>
<td>1450</td>
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<td>-4943</td>
<td>5110</td>
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<td>-52441</td>
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<tr>
<td>National</td>
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<td>-15232</td>
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<td>8113</td>
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Table 5. The decomposition of regional output - yearly changes in ‘000 of real €, 1995-2001 and selected regions

<table>
<thead>
<tr>
<th>Year</th>
<th>ΔY,</th>
<th>Productivity (z, t * ΔTFP,)</th>
<th>Reallocation (TFP, t-1 * Δz,)</th>
<th>Covariance (ΔTFP, * Δz,)</th>
<th>Entry</th>
<th>Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Firms</td>
<td>Dom</td>
<td>MNEs</td>
<td>All Firms</td>
<td>Dom</td>
<td>MNEs</td>
</tr>
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<td>1999</td>
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<td>-8501</td>
<td>-21722</td>
<td>-30233</td>
<td>-2442</td>
<td>-209</td>
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<tr>
<td>2001</td>
<td>13551</td>
<td>281</td>
<td>-1445</td>
<td>-1165</td>
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Table 6. Econometric results – productivity changes of domestic firms

<table>
<thead>
<tr>
<th>Dep var: $\Delta TFP$</th>
<th>Herfindahl $^a$</th>
<th>MNEs Horizontal$^a$</th>
<th>MNEs Forward$^a$</th>
<th>MNEs Backward$^a$</th>
<th>Year of incorp.</th>
<th>Country dummies</th>
<th>Industry dummies</th>
<th>Time dummies</th>
<th>N. of obs.</th>
<th>Wald $\chi^2$ of joint signif.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.84 (1.37)</td>
<td>1.16*** (.36)</td>
<td>1.13 (.79)</td>
<td>-1.51*** (.49)</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>33644</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.25*** (.33)</td>
<td>1.68** (.69)</td>
<td>-1.71*** (.52)</td>
<td>-.07* (.04)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>33289</td>
<td>***</td>
</tr>
</tbody>
</table>

Semi-robust standard errors in parentheses, clustered for region-industry pairs

***,** or * significant at the 1, 5 or 10 per cent level

$^a$ Lagged one year