Foreign ownership and domestic entry

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Because of the important role of foreign direct investment (FDI) in the proces of globalisation, and the positive effects ascribed to it, the impact of inward FDI on domestic economies has attracted much attention from academics and policy makers. The most recent World Investment Report (UNCTAD, 2014, p. 109 ff.) notes that many countries continue to use financial, fiscal and regulatory incentives to attract investment from multinational companies. Job creation is mentioned as the most important reason for attracting investment; technology transfer and linkages with the local economy are other important reasons. Notably, the report also mentions that the effectiveness of these programs is questionable, saying that "*such schemes have been criticised for being economically inefficient and leading to misallocations of public funds*."

These policy issues are mirrored in the academic literature on FDI, where the identification and measurement of consequences of investment by foreign-owned firms in the local economy is a major question. Many studies find that multinational firms are on average more productive than local firms (see for example the discussion in Bernard et al. 2011, section 9), and researchers have proposed a number of channels through which this productivity advantage may spill over to local firms. Spillovers may come about through increased competition; linkages between industries in the supply chain (eg, better inputs); demonstration or imitation effects; learning to export; or labour mobility. Some of these channels can also have negative effects on local firms: increased competition can force local firms to exit, or multinationals may hire the most productive employees.

Motivated by the availability of firm level data and new insight into the importance of firm level heterogeneity (particularly productivity differences) for trade and FDI (Helpman, Melitz and Yeaple 2004; Melitz 2003) the empirical literature on spillovers from foreign investment has focused most of its attention on the measurement and explanation of productivity effects at the firm level to analyse if and how FDI has any effects on domestically owned firms in the host country. A related line of research studies how FDI impinges on entry of domestic firms, but this body of literature is less developed. There are nevertheless good reasons to study entry. First, a focus on productivity effects in existing firms due to FDI —the intensive margin— can mask effects at the external margin, for example when FDI enhances performance of existing firms at the expense of start-ups. Second, although entry is an imperfect proxy for productivity, it also has important practical advantages: Rosenthal and Strange (2003) argue for the study of firm entry because it obviates the need for input variables to measure productivity; new establishments are relatively unconstrained by previous decisions; and new firms make decisions taking the existing environment as given, diminishing concerns of endogeneity due to simultaneity. Third, entry is an important driver of economic growth and productivity change at the aggregate level (eg, Audretsch and Keilbach 2004; Foster, Haltiwanger and Syverson 2008), and is therefore of interest in itself.

The current literature on FDI and entry of domestic firms —which we discuss at length in Section 1— consists largely of studies of individual countries, with a focus on industry-level determinants of entry. Concurrently, work in regional economics and economic geography points to the importance of regional economic conditions for productivity and entry. For example, Head and Mayer (2004) show that regional economic size is an important determinant of location decisions for foreign investors in Europe. If such regional factors also effect the location decision of new domestic firms (as for example in Rosenthal and Strange 2003), not controlling for regional characteristics would bias our estimates of the relation between FDI and new domestic firms.

While this may not be of great concern to studies of single countries, where there is relatively little regional variation and country characteristics are implicitly controlled for (but see Merlevede and Purice 2015, for an example where regional variation in a single country is found to be important), it is very relevant to our current work. The main contribution of our work is that we extend the analysis to fifteen continental European countries, and estimate the relationship between domestic entry and foreign investment at detailed regional level. From our data, we observe the location of foreign and domestic firms at the regional level, as well as the industrial sectors in which these firms are active. This allows us to control for a number of relevant regional characteristics, as well as industry level measures that have been used in earlier studies. As our data have a panel structure, we can also control for unobserved heterogeneity in industry-region characteristics. Estimating at the regional level is important for at least two reasons. First, aggregation to higher geographic levels hides a lot of variation. We come back to this point in Section 2.2. Second, spillovers effects from foreign owned firms may dissipate with distance. Aggregate analysis would then miss all or part of these spillover effects. Indeed, we find some indications that this is the case in our data.

A further contribution of our work is that we explicitly control for barriers to entry at the industry level by including the productivity cut-off in our regressions. The productivity cut-off plays an important role in models of firm entry. For example, in Melitz (2003) or Asplund and Nocke (2006), the productivity cut-off is directly related to the fixed cost of entry.

Our results consistently show a positive effect of FDI on the entry of domestic firms. When looking at spillover effects along the value chain, we find that FDI in upstream industries explains much of this effect. We also find that foreign firms that entered the local market between two and three years ago have a stronger positive effect than both the foreign firms that entered more recently, and those that entered longer ago. This suggests that spillover effects take some time to develop, but also that entry is a short to medium term adjustment, rather than a change in the level of firm turnover. However, we find little evidence for the hypothesis that effects are heterogenous with respect to FDI firm size or country of origin.

The remainder of this paper documents the following: in Section 1, we review the literature on the effects of FDI on indigenous firms host economies in more detail, focusing mainly on the relation between entry and FDI. Section 2 discusses our estimation methodology and describes the data. The results of the study are in Section 3. Section 4 concludes.

1 Literature

The empirical literature on the effects of foreign investment on domestic firms is extensive. In our review of the literature, we make a distinction between studies that try to estimate the effect of foreign presence on productivity; and studies that use other indicators such as entry, exit or growth of firms. Given that the latter group is more closely related to our study, the discussion will focus on the latter group.

1.1 Productivity spillovers

Following Aitken and Harrison (1999), a large share of recent studies on the spillover effects of foreign-owned firms on domestic firms try to measure productivity at the firm-level, and test whether domestic firms are more productive in the presence of foreign firms. Since Javorcik (2004) found that spillover effects for Lithuania were strongest for the suppliers of foreign firms, researchers distinguish within-industry (horizontal) spillovers and spillovers along the supply chain (vertical spillovers), which can again be subdivided into forward and backward spillovers. Havránek and Iršová (2011) and Iršová and Havránek (2013) report on extensive meta-analyses of this literature. They find that horizontal spillovers are zero on average, although there is some variance in the spillover effects. For vertical spillovers, Havránek and Iršová do report positive spillover effects, but mainly for firms in supplying sectors, in line with Javorcik's initial finding. Research has also uncovered mechanisms that mediate spillover effects, such as the absorptive capacity of local firms (Damijan et al. 2013), technology and embeddedness of the foreign firm (Giroud, Jindra and Marek 2012), timing effects (Merlevede and Purice 2015; Merlevede, Schoors and Spatareanu 2014) and firm size (Lenaerts and Merlevede 2015).

1.2 Other indicators

Compared to the number of studies linking FDI to productivity in domestic firms, there are few studies that try to explain the relationship between FDI and other indicators such as entry, exit or growth.

Görg and Strobl (2002a,b) study the case of the manufacturing industry in Ireland for respectively 1974–1995 and 1973–1996. In one study, Görg and Strobl aggregate plant-level entry data to construct yearly (net and gross) entry rates for eight broad manufacturing sectors. From a panel model with fixed effects for sectors and years, they conclude that the presence of plants of multinationals indeed stimulates entry of domestic firms. In a follow-up study, the same authors study employment in entering firms. Start-up size is negatively effected by multinational firms, and more so for relatively large entrants. The effect is also more negative for firms in sectors Chemicals, Metal and Engineering, and Other Manufacturing. For the case of Ireland, it seems that FDI stimulates more entry of smaller firms. The net effect of this is not clear. In a third study on Irish manufacturing industries, Barrios, Görg and Strobl (2005) find that the effect of FDI on entry of domestic firms is not monotonous: at low levels of foreign investment, domestic entry is deterred, but the effect increases with the level of FDI, and turns positive where the share of foreign firms is above approximately twenty per cent.

De Backer and Sleuwaegen (2003) estimate entry and exit of firms for Belgian manufacturing industries for 1990-1995. FDI hinders entry and stimulates exit, but there is some evidence that the negative effect may be moderated in the long term. De Backer and Sleuwaegen hypothesise that positive effects may take some time due to learning and the establishment of linkages, but do not have the data to test this.

For manufacturing in Greece, Fotopoulos and Louri (2004) find that spillovers from foreign owned firms affect growth of total assets of domestic firms positively. A more recent study by Kosová (2010) for the case of the Czech Republic (1994-2001) looks at the growth rates of sales. She finds support for a negative short-term effect at entry of a foreign firm, but a positive effect in the long run as the foreign owned firms grow. The same conclusion follows from Kosová's analysis of survival rates of domestic firms. Another study for the case of the Czech Republic by Ayyagari and Kosová (2010) examines entry rates, and find a positive effect of FDI on domestic entry that is stronger for services than for manufacturing, and for FDI that originates within the EU than for other nationalities. Ayyagari and Kosová also construct measures of FDI for upstream and downstream sectors, as is commonly done in productivity-based studies; the evidence for vertical spillovers is rather weak. This is surprising, since vertical spillovers are usually found to have strong effects for productivity.

Finally, the study by Danakol et al. (2013) looks at a sample from many different countries. They use data from the Global Entrepreneurship Survey that is conducted in mote than 70 countries. In this respect, they differ from the studies mentioned above, that mostly use firm-level accounts to construct data. Also, Danakol et al. look only at cross-border mergers as their source of foreign presence. For the period 2000 to 2009, they find that entrepreneurial activity is stymied in countries with more cross-border mergers.

All in all, the evidence is mixed. While for TFP, there is currently some consensus that are positive vertical spillovers from FDI, there is no such agreement for other measures. It is moe common that researchers find positive effects, especially in the longer run and in European countries, but this finding does not seem to be very robust.

2 Estimation methods and data

We view our analysis of the entry of new firms as a problem of location choice. Building on the results by McFadden (1974) and Carlton (1983), empirical models of location choice can be derived from a theoretical framework of random profit maximisation by investors. If investor i, active in sector s in region r has profits $\pi_{irs} = \beta' x_{rs} + \epsilon_{irs}$ (where x_{rs} is a vector of regional and sectoral covariates), and ϵ_{irs} follows an extreme value II distribution, the probability that i will enter in region r and industry s can be estimated by conditional logit regression. Guimarães, Figueiredo and Woodward (2003) and Schmidheiny and Brülhart (2011) show that the likelihood function resulting from the conditional logit model is equivalent to that of the Poisson model, and that the parameters can be given the same interpretation. Alternatively, Becker and Henderson (2000) derive the Poisson regression from a model where each region has a certain number of 'latent entrepreneurs' that are immobile across regions, and decide to enter the market when the expected profits from doing so are positive. The estimates from a Poisson regression are thus compatible with both models of entry.

Besides these theoretical underpinnings, the Poisson model deals naturally with a number of empirical issues in our data. A count of new firms is necessarily a non-negative integer number. Also, a significant share of observations has zero entry of new firms (see also the discussion in Section 2.2 and Table 2). The non-negativity constraint and the probability mass at zero violates assumptions underlying standard linear panel models, leading to bias in the estimates from such models. A common choice is to treat zero values as a corner solution and estimate a Tobit model. However, conditional fixed effects Tobit models are not currently available (see below for further discussion). Linear models that assume an exponential mean function can handle the non-negativity constraint, but require ad hoc solutions for the values at zero (as log (0) is not defined). The Poisson model explicitly takes into account that the dependent variable is distributed as non-negative integers. Non-linear least squares also offers no advantages over the Poisson model (see the discussion in Winkelmann 2008, Ch. 3).

Second, the Poisson regression model assumes that the event of an investor entering the market occurs randomly and independently over time. An important case that violates this assumption is the presence of persistent effects in regions or industries, which would create time dependence in the entry counts. While we can control for some observable characteristics of regions and industries, it is likely that important characteristics are not observed by us. Certain regions could for example attract many new entrepreneurs due to an entrepreneurial local culture, or a sector can spawn new firms due to processes that are not fully captured by traditional measures of market structure (e.g., Audretsch and Keilbach 2007; Doepke and Zilibotti 2013). To the extent that these effects are constant in the region-industry, the panel structure of our data allows us to control for such unobserved heterogeneity by applying the fixed effects Poisson (FEP) estimator (Wooldridge 2010, section 18.7.4). This, in our view, is a strong advantage that Poisson models have over Tobit models that also deal with the issue of zero counts. At present and to our knowledge, there is no conditional Tobit model available that estimates fixed effects. Although one could estimate a model with dummies for all region-industry pairs, there are two problems with this. First, since the number of dummies would be very large (930 regions$\times$ 43 industries), this would be computationally difficult. Second, even if this were possible, estimating all dummies would lead to an incidental parameter problem for Tobit models (although the nature and size of this bias is not very clear; see Greene 2004). Incidentally, this issue does not apply to Poisson models.

A further issue is equidispersion: the Poisson model requires that the conditional mean of the dependent equals its variance. This condition rarely holds; in most data the variance is larger than the mean (ie, there is overdispersion). Consequentially, the distributional assumptions of the Poisson are incorrect. However, Wooldridge (1999) shows that the fixed effects Poisson pseudo-maximum likelihood (FEP-PML, or simply PPML) estimator gives consistent point estimates for coefficients if the conditional mean is correctly specified. Overdispersion does not affect consistent estimation of the parameters in the mean function, but does lead to incorrect standard errors, and thus to incorrect inference. Wooldridge also shows how a robust estimate of the variance can be constructed, on which inference can be based. This PPML estimator is used often in the estimation of gravity models in international economics for partially overlapping reasons

(Santos Silva and Tenreyro 2006; 2010). Also see Brülhart, Jametti and Schmidheiny (2012) for a recent application of the PPML in a location choice context. Santos Silva and Tenreyro (2011) also show that the PPML estimator performs well with data where a very large share of the dependent variable has value zero. Although other models such as the negative binomial model, the exponential regression model or non-linear least squares outperform PPML in specific cases, PPML has relatively small bias in most cases, and performs well on average. Moreover, fixed effects estimators for these alternative models are not readily available or are inadequate for our purposes (see for example Allison and Waterman 2002).

Taking these issues into consideration leads us to specify our model as in Equation 1. Our analysis is at the region-industry-year level; t indexes years, s indexes industry sectors and r regions. The vector $\mathbf{X}_{srt}$ consists of control variables and a full set of year dummies; the c_{sr} are unobserved.

$$\begin{aligned} f(y_{srt}|\mathbf{X}_{srt}, c_{sr}) &= \frac{\exp\left(-\lambda_{srt}\right)) \times (\lambda_{srt})^{y_{srt}}}{y_{srt}!} \,, \\ \text{with } \lambda_{srt} &= \mathrm{E}[y_{srt}|\mathbf{X}_{srt}, c_{sr}] = c_{sr}\exp(\mathbf{X}_{srt}\beta') \end{aligned} \tag{1}$$

We assume y_{srt} and $y_{srt'}$, $t \neq t'$, are independent conditional on $\mathbf{X}_{sr\cdot}$ and c_{sr}, but place no restrictions on the correlation of $\mathbf{X}_{srt}$ and c_{sr}. Hausman, Hall and Griliches (1984) show how the individual effects c_{sr} can be eliminated by conditioning on the individual sum of counts $\sum_{t=1}^{T} y_{srt}$. Wooldridge (1999) shows that this estimator is consistent for β if $\mathrm{E}[y_{srt}|x_{srt}, c_{sr}]$ is correctly specified, even if $f(y_{srt}|x_{srt}, c_{sr})$ is not, and constructs a robust estimate of the variance. The model is estimated using maximum likelihood methods. Coefficients can be interpreted as semi-elasticities: $\frac{\partial \mathrm{E}[y|\mathrm{X}]/\mathrm{E}[y|\mathrm{X}]}{\partial x_k} = \beta_k$, which —unlike the marginal effects $\frac{\partial \mathrm{E}[y|\mathrm{X}]}{\partial x_k}$— are constant for all observations and do not depend on the value of $\mathbf{X}$. Also, because the marginal effects depend on c_{sr} through $\mathbf{X}$, and c_{sr} are not estimated, the marginal effects are not identified.

2.1 Definition of variables

We define a firm as an entrant if the year of incorporation coincides with the year of observation. Our data does not have a complete record for all firms over time, so entry in the data set is insufficient to conclude actual entry in the economy. We define a firm as foreign-owned if there is at least one foreign firm that owns fifty per cent or more of that firm, and use a ten per cent ownership cut-off in a sensitivity analysis. Most foreign-owned firms are majority owned, so different definitions of foreign-firms have only small effects on our results, as we will see later.

The main explanatory variables are the number of foreign firms and the number of domestic firms in a region-industry. We also estimated all models with total foreign and domestic employment rather than firm counts, and counts and employment jointly. In all models, firm counts had stronger and more significant results, so we decided to focus on those variables. Most existing work estimates models using the share of foreign firms (or employment, or output) as a dependent variable, and the share of foreign firms as an explanatory variable. We estimate in absolute counts; controlling for the number of domestic firms is then important to account for scale effects, and has the advantage that we do not constrain the coefficients, as one would when estimating ratios.

In our regressions, we further control for a number of region and industry characteristics. At the industry level, we are mostly concerned with differences in competition and barriers to entry between different industries. We control for this using the TFP cut-off for each industry. This TFP cut-off plays a prominent role in models dealing with entry, exit and growth of heterogenous firms such as Jovanovic (1982) or, in an international context, Melitz (2003). In these models, the combination of fixed entry costs and uncertainty about productivity draws from a known distribution generates a cut-off value for productivity. Firms with productivity below this value exit (or do not enter) the market. The observed cut-off value for TFP should thus be a good proxy for unobservable barriers to entry, with higher cut-off levels leading to lower entry. We compute TFP for all domestic and foreign firms using the methods described in Wooldridge (2009), who elaborates on the work of Olley and Pakes (1992) and Levinsohn and Petrin (2003). We then define the cut-off level as the first decile of this distribution. For further robustness tests, we also use average firm size and a standard Hirschman-Herfindahl Index (HHI) as controls; see section 3.1 for further explanation. All three variables are constructed at the national level (for each industry) rather than the NUTS 2 or NUTS 3 level, as results at the regional level were very volatile and had many missing values.

At the regional level, GDP and Population control for the local market size. We expect both to have a positive effect on the number of new establishments. Unemployment and the Wage level are included to control for labour market effects. We measure the wage level as the ratio of total hours worked, and total labour expenditures in a region. Both measures are measured at the more aggregated NUTS 2 level, for lack of data for NUTS 3 regions. The effect on the number of new establishments for these variables is not clear a priori. High levels of unemployment could lead to more new firms because it indicates a surplus of local labour supply, or because the unemployed are more inclined to start their own business. Alternatively, high unemployment may indicate unfavourable economic conditions to start new business. The wage level is both an opportunity cost for local entrepreneurs in terms of foregone wages, and an operating costs for firms, and should thus affect entry negatively. For more general business cycle effects, we include GDP growth and a full set of year dummies.

Table 1: Countries in data

	Regions		Regions
Austria	35	Hungary	20
Belgium	44	Italy	106
Czech Republic	14	Netherlands	40
Germany	429	Poland	66
Spain	48	Portugal	28
Finland	19	Sweden	21
France	96	Slovakia	8

'Regions' is the number of NUTS 3 regions within the country.

2.2 Data

Our data are based on combined versions of Bureau Van Dijk's Amadeus database that has information at the firm level for a large number of European countries. We have data for a large share of continental European countries for the period 2003–2007. Although we can construct firm counts for the UK and Ireland, we cannot compute TFP for firms in those countries. Also, we exclude Estonia, Slovenia, Greece, Lithuania and Latvia, Cyprus, Malta and Luxembourg from the analysis because of a lack of data for one or more variables for these countries. Table 1 lists the countries in our data, together with the number of NUTS 3 regions within each country.

From this data, we can determine the date of incorporation, foreign or domestic ownership percentages, and size of the firm in terms of employment and sales. Also, we know the NUTS 3 region where a firm is located, and the 2 digit NACE code for the industry in which the firm has its main activity. We then aggregate the firm-level data on entry and the stock of domestic and foreign firms to the NUTS 3 and the NUTS 3-NACE level. For robustness checks and other models, we aggregate further to the NUTS 2 level. We discard agriculture, mining, education, health, financial services and public services sectors from the analysis. All in all, we can use 930 NUTS 3 regions, and 43 sectors. Since we rely on fixed effects models for identification, individual region-industry combinations without variation over time are also dropped from the analysis. We assume that region-industry combinations that logically exist but are not observed in our data have zero entry and zero existing firms, and we fill out the data accordingly. Note that the FEP estimator is constructed in such a way that region-industries that have zero entry throughout (ie, $\sum_{t=1}^{T} y_{srt} = 0$) do not bear on the likelihood; filling in the data is therefor not as consequential as one might think. The data for the regional control variables are taken from the

Eurostat database and the Cambridge Econometrics regional data. Merlevede, De Zwaan et al. (2015) discuss the firm level data and the construction of the data set in detail.

Combining different editions of the Amadeus data has several advantages. First, although each edition has information going ten years back, firms that exit the market are deleted from the Amadeus records for all years. This makes it difficult to track entry from a single edition. Second, unlike the financial data that do vary over time within a single edition, ownership information does not. Combining different editions allows us to identify when ownership information changes, effectively making foreign ownership vary over time. Not only does this make the data more reliable; it also allows us to exploit information on timing, as we do in one of the extensions of our model.

In section 3.2 we use input-output (IO) tables provided by Eurostat. We use national input-output tables for 2005, except for Hungary where national tables are not provided, and we use the EU-wide IO tables. These tables are available at five year intervals.

Table 2 shows summary statistics for the most important variables in our analysis. In the top panel (labeled A), we show summary statistics for entry of domestic firms and the number of foreign and domestic firms at different levels of regional and industry detail. Rows labeled 'NUTS 2/NUTS 3' are for the obvious regional level, and aggregate over all industries; rows labeled 'NUTS 2,3-NACE ' give statistics per region-industry. These statistics are pooled for 2003-2007. It is clear that the data are right-skewed for all variables, especially at the NUTS 3-industry level: many observations have zero counts, and the variables have long right tails. Even at the NUTS 2 level and aggregating over all industries, we observe regions that have only a small number of domestic firms, and no entry of foreign firms . As discussed in Section 2, the FEP estimator we employ deals with these issues naturally. Even aggregating up to the NUTS 2-NACE level would not solve the issue of the heavy probability mass at zero. While numbers are better for the region-level (rather than the industry-region), analysis at the regional level would lump together all industry-specific variation.

In the bottom panel of Table 2 (B), we give statistics for control variables and again for entry and firm counts. We restrict the data to the observations used for the estimation of the full model in Table 4 (Column 4), which serves a basis for further analysis. By construction, region-industries that have zero entry for all years do not enter the likelihood function, and are thus effectively removed from the sample. These regions generally have a low firm count, both for foreign and domestic firms. This explains why average entry and firm counts are higher in panel B than in panel A.

To quantify the importance of regional disaggregation, we compute three different measures of standard deviation of entry and the foreign firm counts for the NUTS 3 regions: between (ie, the cross-sectional variation in NUTS 3-level means), within time (ie, the average variation of

Table 2: Summary statistics

	Mean	St. dev.	Min	p25	Median	p75	Max	% 0
	A: Entry & firm counts							
NUTS 3-NACE (N = 224100)								
Entry	0.56	6.1	0	0	0	0	859	88
Domestic firms	69.87	369.2	0	1	6	30	26159	22
Foreign firms	0.79	7.5	0	0	0	0	554	82
NUTS 3 (N = 4980)								
Entry	26.65	108.7	0	2	6	15	3050	11
Domestic firms	3180.51	6603.3	5	594	1281	3155	97540	0
Foreign firms	35.47	107.6	0	3	9	23	1624	8
NUTS 2-NACE (N = 42750)								
Entry	2.94	15.9	0	0	0	1	859	70
Domestic firms	360.70	1252.7	0	7	41	192	53055	11
Foreign firms	4.10	24.7	0	0	0	2	978	56
NUTS 2 (N = 950)								
Entry	139.55	265.5	0	12	46	138	3050	4
Domestic firms	16420.55	20441.5	179	4823	10449	20635	213854	0
Foreign firms	185.12	339.0	0	21	71	169	2856	2

	Mean	St. dev.	Min	p25	Median	p75	Max
	B: Summary statistics (NUTS 3-NACE)						
Domestic entry	2.25	12.1	0	0	1	1	859
Foreign firms	2.44	14.0	0	0	0	1	554
Domestic firms	205.07	634.4	0	15	48	160	23097
TFP cut-off	9.38	1.1	1.74	9.11	9.58	9.97	13.92
GDP (mio.)	486.81	573.7	21.09	165.19	304.35	600.91	5988.95
ΔGDP (%)	0.19	0.7	-2.83	-0.18	0.13	0.49	4.71
Population (×1 000)	486.80	573.7	21.09	165.19	304.35	600.91	5988.95
Unempl. rate (%)	9.19	5.0	1.80	5.80	8.00	10.60	26.60
Wage level	14.66	6.3	1.91	12.08	15.99	18.46	31.29

Columns 'p25'and 'p75' refer to the 25th and 75th percentile respectively. Panel A: Figures are pooled for 2003–2007, using the full sample. Column '% 0' shows the percentage of observations with a zero count for the respective variable. Panel B: N = 54 625, based on the sample used for the full model (Column 4) in Table 4.

Table 3: Industries and regions with highest/lowest shares of foreign firms

NUTS 3	% Foreign	NACE	% Foreign	NACE	% Foreign
PL127	13.7	DF23	9.1	KA70	0.5
PL12A	13.1	DG24	7.2	DD20	0.5
PL418	12.4	DM34	6.0	EA41	0.5
PL431	11.0	DE21	4.4	GA52	0.5
PL518	10.5	CA11	4.1	DC19	0.4
PL332	9.7	DM25	3.7	IA60	0.4
DE139	8.8	DL30	3.6	HA55	0.2
PL423	8.8	DL32	3.5	FA45	0.2
AT127	8.7	DL31	3.5	DA16	0.0
DE712	8.2	IA62	3.4	CB13	0.0

NUTS 3 codes for regions with highest share of foreign firms in the sample in first two columns; NACE codes for industries with highest share of foreign firms in center columns; and for industries with lowest share in last two columns. Figures are for the median of the share of foreign firms in the total number of firms, computed over all years in the sample.

NUTS 2 counts about their means), and within region (ie, the variation of counts for NUTS 3 regions within each NUTS 2 region). Denote these sd_b, $\mathrm{sd}_{w(t)}$ and $\mathrm{sd}_{w(r)}$, respectively. For counts of entry, we find that $\mathrm{sd}_b = 9.35$, $\mathrm{sd}_{w(t)} = 3.84$, and $\mathrm{sd}_{w(r)} = 1.43$. For the count of foreign-owned firms, we find $\mathrm{sd}_b = 10.91$, $\mathrm{sd}_{w(t)} = .5.58$, and $\mathrm{sd}_{w(r)} = 3.24$. Note that, since we estimate using fixed effects, we restrict ourselves to information from within time variation. The within-region variation is sizeable, approximately 35 per cent of within time variation for entry, and over 55 per cent for the number of foreign firms. This means that aggregating to NUTS 2 level leaves this heterogeneity unexplained.

In Table 3, we present the ten industries with the highest and lowest shares of foreign firms. For regions, we present only the highest shares, since the lowest all have zero shares, as explained earlier. There are seven Polish regions in this top ten (first two columns; 47 out of 66 Polish regions are among the top 100 regions), but we do not see many other Eastern European countries high up in the list. As for industries, the top ten consists mostly of manufacturing industries (codes starting with 'D').

3 Results

Our base line results are presented in Table 4. All models are estimated using Poisson regression with multiplicative industry-region fixed effects as in Eq. (1) and include year dummies. Standard errors are robust. All explanatory variables are lagged one year, under the assumption that entrants in the current year base their decision on the situation in the last year. We present in Column (1) a model without any control variables other than the focal variables, the count of foreign and domestic firms in the region-industry. We proceed by adding variables that vary at the country-industry level in Column (2), variables that vary only at the region level in Column (3) and finally the full set of controls in Column (4). For all models, we restrict the data to the sample used for the full model, to ensure that any differences are not due to missing values for some of the variables. Note that in these tables counts of foreign and domestic firms are measured in hundreds for presentational reasons.

Comparing Columns (2) and (3) shows that regional characteristics are important determinants of entry of new firms, and not controlling for these characteristics strongly influences the results.

From Table 4, Column (4), we find positive and significant coefficients for both the count of foreign firms and the count of domestic firms, implying that larger region-industries attract more new entrants. Coefficients can be interpreted as semi-elasticities: comparing two region-industries where in year t one region has 100 more foreign firms than the other, the region-industry with more foreign firms would on average expect to have 17.7% (95% CI: $[2.4, 33.0]$) more domestic entrants in $t+1$. This effect also holds for domestic firms, in which case the larger industry would expect to see 1.1% $[0.1, 1.5]$ more domestic entrants. However, as is clear from Table 2, differences of 100 foreign firms are not common for the stock of foreign firms, while they are very common for domestic firms. A one standard deviation increase of 14 foreign owned firms —roughly equivalent to the average difference for Wholesale (NACE 51) and Manufacture of food and beverages (NACE 15) in 2006 in France— gives a 2.5% increase, which seems more plausible. A standard deviation change for the number of domestic firms is associated with a 7.0% change in the number of entrants.

Although foreign firms impact entry of domestic firms positively, this effect is smaller for foreign than for domestic firms. A possible explanation is that both types of firms have positive spillover effects, but that the competitive effect is stronger for foreign firms, leading to a less positive net effect. This seems more reasonable than the hypothesis that foreign firms have smaller positive spillover effects, as research generally finds that only the most productive firms invest abroad.

The findings for most of the control variables are as expected, with the exception of Population size and the Wage level. In line with theory, the TFP cut-off has a negative effect on entry. GDP

Table 4: Entry of domestic firms

	(1)	(2)	(3)	(4)
Foreign firms	-0.069	-0.045	0.154 **	0.177 **
	(0.09)	(0.10)	(0.07)	(0.08)
Domestic firms	0.011 ***	0.011 ***	0.011 ***	0.011 ***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP cut-off		-0.030 ***		-0.028 ***
		(0.01)		(0.01)
GDP			1.227 ***	1.201 ***
			(0.18)	(0.18)
Population			-1.231 ***	-1.206 ***
			(0.18)	(0.18)
Unempl. rate			-0.037 ***	-0.036 ***
			(0.01)	(0.01)
Wage level			0.299 ***	0.303 ***
			(0.02)	(0.02)
ΔGDP			5.157 ***	4.650 **
			(1.83)	(1.83)
Obs.	54625	54625	54625	54625
LL	-41981	-41963	-41389	-41373

Robust standard errors in parenthesis. *, **, and *** indicate $p < .10$, $p < .05$ and $p < .01$, respectively. All models are estimated at the region-industry level conditioning on region-industry fixed effects and include year dummies. See text for more details.

affects entry positively, indicating that high GDP regions are attractive locations; this is in line with the literature on agglomeration and economic geography. Population, however, has a negative effect. One reason could be that high population (for given levels of GDP and the stock of firms) lead to congestion costs that make entry unattractive. For example, land prices and real estate could be costly in more populated areas. We have no clear priors for the effects of the unemployment rate. In our data, higher unemployment is associated with lower entry. Most problematic is our finding that, contrary to standard theory, a higher wage level leads to more entry. Of course, the measurement of wages is crude, as we have no information on the kind of labour employed by new firms, nor on the wages for those different subgroups. Finally, GDP growth positively affects entry.

3.1 Alternative specifications

Columns (1)–(3) in Table 5 document the results from different robustness tests. One concern is that our standard errors are biased. Our control variables are measured at different levels of aggregation. Moulton (1990) argues that standard errors should be clustered at the highest level of aggregation for correct inference. Since clustering is not straightforward for the FEP model, we report bootstrapped standard errors (1000 draws) in Column (1). Results change only minimally.

In column (2) we add further control variables. We add two more controls for competition or barriers to entry: the Hirschman-Herfindahl Index (HHI), measured as the sum of squared market shares in terms of revenue of all firms in a country and industry, and Average firm size (in terms of employment). The HHI is a standard measure for competition, ranging from zero for very competitive industries, to unity for a monopoly. We also include Average firm size. Average firm size should control for differences in technological characteristics specific to the industry. Large average firm size can be interpreted as an indicator for low levels of competition and high barriers to entry. Entry levels should be higher where average firm size is lower.

We also control for a measure of Market Potential. One of the main findings in the economic geography literature is that economic size is determined not only by market size of a region (proxied by GDP), but also by the market size of other regions, weighted by the access a region has to those other regions. We define our measure of Market Potential as the distance-weighted sum of GDP in all other regions (Harris 1954). Head and Mayer (2004) use a measure of market potential based on trade flows, but the requisite interregional trade data are not available at the regional level. Moreover, Head and Mayer conclude that the Harris type measure is a reasonable approximation.

Both competition measures give insignificant coefficients. Market Potential has a negative sign, which is not in line with standard theory in economic geography. Note however that our measure excludes own GDP, for which we control separately. The joint effect is positive. More importantly for our argument, neither added control changes the results considerably. The main change is that the coefficient on GDP growth is much smaller and no longer significant. From unreported models where we add the competition measures and Market Potential separately, it becomes clear that this effect is largely due to the latter. Coefficients for the stock of foreign and domestic firms change only very slightly.

Columns (3) and (4) use different definitions for some of our variables. Before, we measured the TFP cut-off at the 10th decile, we now measure at the 25th, with very little changes compared to our main model. We also check whether results are robust to different definitions for foreign firms. Before, we identified a firms as foreign if it was more that 50 per cent foreign owned. In column (4) we report results for a 10 per cent cut-off. The coefficient for foreign firms is now smaller by two percentage points, but still positive and significant at five per cent. Models with 'foreign' defined at 25 per cent gave intermediate results.

In the rightmost two columns, we use different samples of our data. Column (5) reports results for the subsample of region-industry-years that have positive entry (recall that region-industries that never have positive entry in our data have no weight in the model in any case). For this subsample, the coefficient for foreign firms is slightly smaller, but no longer significant at the five per cent level. Signs and significance levels for the other variables are largely unchanged, with the exception of the coefficient for Average firm size that is now significant. Finally, in Column (6), we report results from our standard model, but estimated at the NUTS 2 level of aggregation rather than at NUTS 3. In this model, the effects of both foreign and domestic firms are much smaller, and, in the case of foreign firms, no longer significant at conventional levels. We interpret this as an indication of the attenuation of spillover effects over distance. Although our data do not allow us to investigate this issue with the precision of Rosenthal and Strange (2003), our result does indicate a similar proces of distance decay could be at work.

3.2 Extensions

Results show far point to a positive effect from foreign firms on entry of domestic firms. In this section, we try to uncover any heterogeneity in this effect. We partition the stock of foreign firms into different categories, making full use of the firm-level information available in our data. We look first at effects along the value chain , then at firm age, country of origin, and finally at timing effects. Table 6 presents the results. For each of the models, we include also the p-values for F-tests for joint statistical difference from 0 (p_0), and difference from the main coefficient (p_1), ie the coefficient from Column (4) in Table 4.

Javorcik (2004) argues that that the effects from FDI may vary along the value chain, and shows that FDI in downstream sectors (ie, sectors that buy intermediates from the focal sectors) increase productivity of domestic firms more than intra-industry FDI or FDI in upstream sectors. To investigate this for our data, we compute measures of foreign presence in downstream and upstream industries using Eurostat input-output (IO) tables. Define H_{srt} as the share of foreign firms in the total number of firms in each region-industry sr in year t (recall that we define foreign firms as those firms with a majority foreign ownership). Downstream or backward presence B is then the sum of the number of foreign firms for all industries in region r, weighted by the share of output of industry s bought by each industry, and we compute F likewise for upstream or forward industries. Thus (suppressing time indices), if i indexes individual firms, $\mathcal{N}_{sr}$ is the set of firms in sr, N_{sr} is the number of firms in $\mathcal{N}_{sr}$, and S is the total number of

Table 5: Sensitivity analysis

	(1)—Bootstrap	(2)	(3)—TFP: p25	(4)—Foreign: >10%	(5)—entry>0	(6)—NUTS 2
Foreign firms	0.177 **	0.193 ***	0.175 **	0.156 **	0.121	0.034
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.04)
Domestic firms	0.011 ***	0.012 ***	0.011 ***	0.011 ***	0.011 ***	0.008 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP cut-off	-0.028 ***	-0.021 ***	-0.027 ***	-0.028 ***	-0.027 ***	-0.027 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GDP	1.201 ***	0.935 ***	1.214 ***	1.205 ***	0.850 ***	0.207 ***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.05)
Population	-1.206 ***	-0.938 ***	-1.218 ***	-1.209 ***	-0.855 ***	-0.209 ***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.05)
Unempl. rate	-0.036 ***	-0.028 ***	-0.037 ***	-0.036 ***	-0.033 ***	-0.039 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wage level	0.303 ***	0.233 ***	0.300 ***	0.303 ***	0.249 ***	0.258 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
ΔGDP	4.650 **	2.667	4.887 ***	4.620 **	4.694 **	10.112 **
	(1.93)	(1.82)	(1.83)	(1.83)	(1.88)	(4.54)
HHI		0.256				
		(0.20)				
Avg. firm size		-0.000				
		(0.00)				
Market pot.		-0.031 ***				
		(0.00)				
Obs.	54625	54602	54625	54625	20316	18668
LL	-41373	-41257	-41379	-41375	-22603	-21464

Robust standard errors in parentheses. *, ** and *** indicate $p < .10$, $p < .05$ and $p < .01$, respectively. All models are estimated at the region-industry level conditioning on region-industry fixed effects and include year dummies. See text for more details.

industries,

$$
\begin{aligned}
H_{sr} &= \frac{\sum_{i \in N_{sr}} \mathbf{1}(\text{Foreign}_i)}{N_{sr}}, \\
B_{sr} &= \sum_{k=1}^{S} \beta_{sk} H_{kr}, \\
F_{sr} &= \sum_{k=1}^{S} \phi_{ks} H_{kr},
\end{aligned}
\tag{2}
$$

where $\mathbf{1}(\text{Foreign}_i)$ is an indicator function and equals 1 if firm i is foreign-owned. Technical coefficients β_{sk} and ϕ_{ks} are, respectively, the share of sector s's output that is sold to industry k (ie, used as intermediate by k), and the share of s's total intermediate inputs that producers in s buy from k. These coefficients are computed from the 10 tables, excluding imports, exports and final use, so that we focus on local interactions between producers. The coefficients vary over country-industry, but are time invariant (see Section 2.2). Measures H, B and F are included in the regression as described in Eq. (2). Because the number of domestic firms is included in H, we do not include it separately. Since H, B and F are weighted ratios of firm counts, the magnitude of the coefficients cannot be compared directly to Table 4 or 5, and we don't report p_1. Results are in Column (1) of Table 6.

We find no evidence of effects from foreign firms in downstream or upstream industries. Coefficients are all positive, but estimated with little precision, and are not statistically significant. Standard deviatons for H, F and B are respectively 1.8×10^{-4}, 2.9×10^{-4} and 4.5×10^{-4}, so that one standard deviation changes lead to 4.0%, 0.15% and 3.4% changes in entry levels. Jointly, the measures are significant. These results are more or less in line with Ayyagari and Kosová (2010), who also find no evidence of forward or backward spillovers on entry in the Czech Republic.

littlefind a positive effect from upstream investment, and their results are similar to ours for downstream and intra-industry effects.[1]

We also investigated whether coefficients differ between firms of different size classes (in Column 2) and country of origin (Column 3). Lenaerts and Merlevede (2015) find that especially medium-sized firms have a positive impact on the productivity of domestic firms in Romania. In our data, we find no evidence of this effect for entry of new firms. We construct measures for the number of firms with less than 9 employees, 10–49, 5–249 and more than 250 employees.

[1]By including the fraction of output and input that industries buy from themselves in B and F, we depart slightly from the standard definition and follow Lenaerts and Merlevede (2012), who show that this definition gives stronger results. However, a specification where we set $\beta_{ss} = \phi_{ss} = 0$ for F and B, and include $H' = \beta_{ss} H_{kr}$ separately alongside counts of foreign and domestic firms, gives very similar results.

Table 6: Entry: Extensions

	(1)		(2)		(3)		(4)	
Foreign: linkages								
Horizontal	222.745							
	(136.40)							
Backward	77.502							
	(89.41)							
Forward	5.316							
	(20.20)							
Foreign: size class								
1–9			0.089					
			(0.27)					
10–49			0.196					
			(0.40)					
50–249			0.058					
			(0.55)					
>249			1.872	*				
			(0.96)					
Foreign: origin								
Europe					0.188			
					(0.19)			
OECD–not Europe					0.425			
					(0.30)			
Not Eur.–not OECD					-1.788			
					(1.21)			
Foreign: Entry...								
...in $t-1$							0.167	
							(0.11)	
...in $t-2$							0.232	***
							(0.08)	
...in $t-3$							0.303	***
							(0.10)	
...before $t-3$							-0.026	
							(0.13)	
Domestic firms			0.012	***	0.010	***	0.012	***
			(0.00)		(0.00)		(0.00)	
Obs.	54625		54625		54625		54625	
LL	-41504		-41373		-41368		-41362	
p_0	0.01		0.22		0.10		0.00	
p_1			0.42		0.35		0.08	

Robust standard errors in parentheses. *, ** and *** indicate $p < .10$, $p < .05$ and $p < .01$, respectively. Control variables are included in the estimation, but are not reported. All models are estimated at the region-industry level conditioning on region-industry fixed effects and include year dummies. See text for more details.

All coefficients are statistically insignificant at 5%, and are jointly not different from the main coefficient.

For country of origin, we distinguish foreign firms from within Europe, firms from countries that are in the OECD but not in Europe (a category that is dominated by US firms), and from countries that are neither in Europe nor in the OECD. As with size classes, the coefficients are not jointly different from the main effect of foreign firms, and jointly different from zero only with marginal significance.

Finally, we investigate the timing of spillovers. As argued in Merlevede, Schoors and Spatareanu (2014), there are several reasons to expect spillover effects to develop over time. For example, processes such as the diffusion of new technology through imitation and worker mobility or the establishment and optimization of new links with local firms all take time, and one would expect spillover effects to change over time. While it is common to employ lags of dependent variables in the specification, this does not correctly capture such timing effects. As in Merlevede, Schoors and Spatareanu (2014) or Merlevede and Purice (2015), we decompose the count of foreign firms into different cohorts, differentiating between foreign firms that entered the market in $t-1$, $t-2$ and $t-3$, and those that entered earlier (firms observed as foreign at the start of our data are in the last category). Results are in the last column of Table 6. We find a pattern where effects decrease with time: the strongest effect comes from firms that entered in $t-1$, and levels of slightly for $t-2$ and $t-3$. For firms that entered before $t-3$, the coefficient is negative, although no longer significant at conventional levels. Comparisons of the estimates show that the coefficients for entry in the last three years are not significantly different from each other, both that they are jointly and individually different from older foreign firms. This pattern runs counter to the results from Kosová (2010), whose results back up the hypothesis that for productivity of existing firms, FDI has negative spillover effects in the short run but positive effects in the long run.

4 Conclusions

The impact of foreign investment on local development receives a lot of interest from policy makers and academics. Academic work on this topic focuses mostly on productivity spillovers from foreign-owned firms to local, domestically owned firms, and tries to quantify the loss or gain in total factor productivity (TFP) for existing domestic firms due to the presence of foreign firms. This line of research disregards other margins of change, such as entry, exit or growth. In our research, we focus on one of these, and investigate how the presence of foreign firms affects the entry decision of domestic firms.

It is not clear a priori how foreign firms should affect entry of domestic firms. If foreign firms indeed generate productivity gains in domestic firms, more local firms should be able to cross a productivity threshold and enter the market. Conversely, competition from foreign firms can reduce residual demand for new local firms, or —if foreign firms are more productive— can raise the productivity threshold. Although we cannot disentangle the two effects, we can estimate the net effect of the presence of foreign firms.

We quantify the relationship between the stock of foreign firms and the number of new domestic firms on panel data for fourteen continental European countries. At the industry level, barriers to entry are an important concern. We control for this using the TFP cut-off for each industry. We pay much attention to the regional dimension in this issue. Our estimations are at the level of region-industries, and control for unobserved effects at this level. Since we observe many region-industries that have no entry in a given year, we use a Poisson pseudo maximum likelihood that takes this important feature of the data into account. Furthermore, we control for various regional characteristics, and find that they are important to explain entry. Previous studies have mostly focused on industry level controls.

Our main result is that we find a positive effect from the presence of foreign firms, and estimate that for the average region-industry a one standard deviation increase in the number of foreign firms would give rise to approximately 2.5% more domestic entrants in the next year. However, we also find a positive effect from domestic firms, and a standard deviation increase in the stock of domestic firms is is associated with an increase of 7%. These results are robust to a number of different specifications and alternative definitions of our variables.

We then try to probe deeper into these results by splitting up the foreign firms along different dimensions. First, we estimate spillover effects from foreign firms along the value chain. We create measure for foreign firms in downstream and upstream industries, and include these in the regressions. Our results show no systematic evidence of forward or backward spillovers. We also find little evidence that the effect is different for foreign firms in different size classes, or for differences in ownership by origin. Finally, we do find indications that positive effects come mainly from foreign firms that have entered the market two to three years before. Foreign firms that entered have a smaller positive effect; older foreign firms give a slightly negative (but insignificant) effect.

There are two main conclusions we draw from these results. First, we conclude that the presence of more foreign firms make entry of domestic firms in the same region and industry more likely. Nevertheless, the same can be said of domestic firms, and the stimulus from domestic firms seems to be stronger. This result needs to be qualified. We do not differentiate between types of entrant, and foreign firms could for example attract more productive entrants. Nevertheless, the result indicates that perhaps not all foreign firms are ‘special’ in comparison to domestic firms. Second, a more general conclusion is that regional characteristics play an important role in firm entry decisions.

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