Oligopolistic Reaction to Foreign Investment in Discrete Choice Panel Data Models

Carlo Altomonte*

Enrico Pennings†

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Abstract

We offer a simple explanation for oligopolistic reaction based on Bayesian learning by rival firms operating in an uncertain environment. We test the implications of the model through a discrete choice panel data sample of MNEs that have invested in Central and Eastern Europe over the period 1990-1997. Interacting the measure of rivals' investment in country-industry pairs with uncertainty we find strong evidence for oligopolistic reaction, especially through the channel of Bayesian learning postulated by the model. The findings are robust with respect to different model specifications.

JEL classification: C25; D81; F21; L10

Keywords: discrete choice panel data, uncertainty, FDI, oligopolistic reaction

*Università Bocconi and KU Leuven. *Corresponding author:* IEP-Università Bocconi, Via Gobbi, 5, I-20136 Milan. (T)+39.02.5836.5405; (F)+39.02.5836.5439; carlo.altomonte@uni-bocconi.it

†Università Bocconi and IGIER

1 Introduction

Since Knickerbocker (1973), it is well established in the literature on foreign direct investment (FDI) that foreign entry by a firm may lead to rival reaction. The idea is that firms, uncertain of production cost in the country to which they currently export, run the risk of being underpriced by a rival that switches from exporting to establishing a manufacturing subsidiary in the host country. By imitating the rival's FDI, the firm can prevent being underpriced by matching the production cost of the rival firm abroad.

Though it was generally accepted that uncertainty, risk aversion and industry concentration are necessary ingredients for the existence of such an 'oligopolistic reaction' (OR) to foreign investment, only recently a formal theoretical model was put forward by Head, Mayer and Ries (2002). They show that foreign investments by firms in an oligopolistic industry structure are complements if there is cost uncertainty and if firms are sufficiently risk averse. Though their model is elegant, the derivation of the main result poses strong restrictions on both the cost function and on the demand function, i.e. equal costs of production and equal slopes of the demand curves in bothe the home and the host country. Moreover, if firms are not sufficiently risk averse, FDI decisions are strategic substitutes rather than strategic complements[1].

Leahy and Pavelin (2003) provide a more simple explanation for follow-the-leader behavior in FDI decisions. In their model domestic rivals may be motivated to imitate the leader's FDI when it facilitates collusive behavior in the foreign market. Since the result only hinges on the possibility to collude, neither uncertainty nor risk aversion play a role in deriving their main result.

Without identifying the channel through which oligopolistic reaction to FDI arises, empirical literature has confirmed follow-the-leader behavior in FDI decisions (for early contributions see Knickerbocker, 1973, and Flowers, 1976). Controlling for variables relevant for the decision to undertake FDI, such as the market size of the host country and the distance from the investor's home to its host country, Yu and Ito (1988) consider oligopolistic reaction in two types of industries: the US tire and textiles industries. By finding only oligopolistic

[1]Firms actions are strategic complements (substitutes) when an increase in the action of one firm raises (lowers) the marginal benefit of an increase in the action for another firm.

reaction in the tire industry they conclude that firms only react oligopolistically in moderately concentrated industries such as the tire industry and not in the more competitively structured textiles industry.

More recently, Ito and Rose (2002) show that, in the same tire industry, firms like Continental and Bridgestone imitate FDI decisions by leading firms like Goodyear and Michelin. Though their results have a straightforward economic interpretation, they are based on the analysis of only one or two industries while, in order to fully understand the relation between industry-specific characteristics and oligopolistic reaction, a broader analysis seems necessary. Furthermore, oligopolistic reaction is measured in their studies as the impact of the total number of foreign firms (regardless of when they entered) on the probability of investment by another foreign firm in a given year. Since agglomeration effects are often estimated by employing the same variable, a more correct approach to estimating oligopolistic reaction would have been to relate foreign investment to the number of recent new foreign investors. Moreover, as Yu and Ito (1988) suggest for further research, oligopolistic reaction may be cross-border through the effect of global competition on firm's activities.

By examining all Japanese investment into the U.S., Hennart and Park (1994) find evidence that FDI by a Japanese enterprise group in the U.S. is more likely if domestic rivals have already invested in the U.S. For individual firms they do not find supporting evidence for follow-the-leader behavior. Most of the present empirical literature on oligopolistic reaction, however, stresses the role of learning from leading firms, starting with Chang (1995). Successful entry in a foreign country leads to imitative behavior from rival firms.

Along these recent lines of research, the aim of this paper is to set up and estimate a simple model that explains oligopolistic reaction by Bayesian learning from leading firms[2]. The model predicts that oligopolistic reaction is stronger if uncertainty is higher and declines as more and more foreign firms enter. To empirically validate the model, the fall of the Berlin wall in 1989 enables us to monitor over time the number of foreign investments taking place in

[2]Many other studies (e.g. Grossman et al., 1977; Cukierman, 1980; Vettas, 1998) have considered the role of (acquiring) information before making an investment in a Bayesian framework. In particular Cukierman (1980) analyzes the effects of uncertainty on the timing of investment of a risk-neutral firm. These studies, however, examine endogenous information arrival, whereas our approach takes the arrival of information as exogenous.

Central and Eastern European Countries (CEECs). By exploiting the PECODB database[3], our sample consists of the number of European Union's investors in the period 1990-1997 over a large set of industries and the most important CEECs.

By identifying the order of entry from the very first investor to late investors, a panel model can explicitly test for when a foreign firm reacts strategically to other firms' entry. More specifically, oligopolistic reaction is explicitly modeled by relating foreign investment in a given year, industry and country to changes in the total number of investors operating in the same industry and country in the previous year. In addition we test for information spillovers from foreign investors in the previous year in the same industry but in other countries. With the unique sample of firms we estimate a discrete choice panel negative binomial regression model[4].

In particular, Section 2 of the paper presents a simple model of oligopolistic reaction from Bayesian learning whose implications are tested through the econometric approach presented in Section 3. The results are discussed in Section 4, while Section 5 extends the empirical approach by considering learning from investments in other CEECs than the host country. Finally, Section 6 concludes.

2 Oligopolistic reaction FDI and Bayesian learning

Suppose that the cost of production in sector i of country j, c_{ij}, has a prior distribution that is normal with unknown mean w_{ij} and precision parameter r_{ij}[5]. Furthermore, assume that w_{ij} is also normal with prior mean μ_{ij} and precision parameter τ_{ij}. At the beginning of the investment opportunity nature assigns a specific revenue to each firm (1990 in our sample). The firm-specific shock to these revenues, π^f, is randomly drawn from some probability

[3]We are grateful to Sergio Alessandrini at ISLA-Bocconi, Milan for allowing us to exploit the PECODB database, a firm-specific collection of 4,200 FDI operations in the CEECs in the period 1990-1998. In terms of validation, the database is able to account for almost 80 per cent of the region's total FDI inward stock as registered by official statistics. A detailed analysis of the empirical evidence provided by the PECODB database can be found in Alessandrini (2000).

[4]The negative binomial distribution assumption for the number of investors in a year is the most flexible, leaving the Poisson distribution as a special case. In general, previous applications in the field of IO of econometric count models for panel data are rare. An exception is the relationship between firms'investment in R&D and the number of patent applications, starting with the seminal paper by Hausmann et al. (1984).

[5]As it is usual in this literature, the 'precision parameter' is the inverse of the variance.

distribution with mean 0 and is observed by the firm. The revenues of firm f equals $\pi_{ijt}+\pi^f$, where π_{ijt} denotes the mean revenue in industry i of country j at time t. The mean revenue depends on a vector of endogenous variables (X_{ijt}), industry fixed-effects and country fixed-effects.

A risk-neutral firm invests if the revenues from producing abroad exceed the expected cost. Undertaking a FDI resolves the uncertainty surrounding the local production cost of the investing firm. This information then becomes common knowledge to all other potential investors in the same country/industry[6]. Based on this new information, rival firms update their distribution of the production cost according to Bayes' rule. Then the posterior distribution at time t, calculated with the observed production costs of n_{ijt} firms that invested up to time t, is normal with mean

$$\mu_{ijt} = \frac{\mu_{ij}\tau_{ij} + n_{ijt}r_{ij}\overline{c}_{ijt}}{\tau_{ij} + n_{ijt}r_{ij}} \tag{1}$$

where $\overline{c}_{ijt}$ stands for the (observed) average cost of the firms that have invested up to time t. The precision of the posterior distribution, τ_{ijt}, is $\tau_{ij} + n_{ijt}r_{ij}$.

The probability p^f of firm f's investment at time t conditional upon the average cost of the firms that have invested up to time t can be written as

$$\begin{aligned} p^f \mid \overline{c}_{ijt} &= \Pr\left[w_{ijt} < \pi^f \mid \overline{c}_{ijt}\right] = \Pr\left[(w_{ijt} - \mu_{ijt})\sqrt{\tau_{ijt}} < (\pi_{ij} + \pi^f - \mu_{ijt})\sqrt{\tau_{ijt}}\right] \qquad (2) \\ &= \Phi\left((\pi_{ij} + \pi^f - \mu_{ijt})\sqrt{\tau_{ijt}}\right) \end{aligned}$$

where $\Phi(.)$ is the cumulative density function of a standard normal distribution. Hence,

$$p^f \mid \overline{c}_{ijt} = \Phi\left((\pi_{ij} + \pi^f)\sqrt{\tau_{ij} + n_{ijt}r_{ij}} - \frac{\mu_{ij}\tau_{ij} + n_{ijt}r_{ij}\overline{c}_{ijt}}{\sqrt{\tau_{ij} + n_{ijt}r_{ij}}}\right) \tag{3}$$

Suppose that there are no time-effects on revenues, so that revenues are constant over time and denoted by π_{ij}. Then, investment by one firm may trigger investment by another

[6]Given the empirical scope of the paper, we abstain here from related issues such as the rival's decision on sharing information of its costs. Shapiro (1986) provides the condition under which full revelation on cost information is optimal from the firm's perspective.

firm only when the observed production cost is lower than the prior mean of the production cost ($\overline{c}_{ijt} < \mu_{ij}$). If instead observed costs are already higher than a priori expected ($\overline{c}_{ijt} > \mu_{ij}$), there will be no competitive reaction to rival investment. This convexity indicates that uncertainty about expected production cost has a positive effect on the probability of investment by a rival firm in the next period. Without time-dependent revenues there can only exist one cascade of investing firms and later investment can only be triggered by Bayesian learning. When revenues are time-dependent, firms can also invest at a later date for other reasons than Bayesian learning.

The next propositions summarize the effect of uncertainty on investment by analyzing the effect of the precision parameters τ_{ij} (which relates to the variance of expected production cost) and r_{ij} (which relates to the variance of observed production cost) on the propensity to invest, p^f. Moreover, they indicate the role of the number of rival investors n_{ijt} that have invested up to time t.

We start by introducing the following lemma.

Lemma 1 The unconditional probability density function of c_{ij} is normal with mean μ_{ij} and variance $(r_{ij} + \tau_{ij})/r_{ij}\tau_{ij}$.

Proof. Let $\varphi(.)$ denote the probability density function of a standard normal distribution. Then, dropping the industry and country index,

$$\Pr[c_{ij} = x] = \int \Pr[c_{ij} = x \mid w] \Pr[w] dw = \int \varphi((x-w)\sqrt{r})\varphi\left((w-\mu)\sqrt{\tau}\right)\sqrt{r\tau} dw$$

$$= \int \frac{\sqrt{r\tau}}{2\pi} \exp\left(-\tfrac{1}{2}(x-w)^2 r\right) \exp\left(-\tfrac{1}{2}(w-\mu)^2\tau\right) dw$$

$$= \int \frac{\sqrt{r\tau}}{2\pi} \exp\left(-\tfrac{1}{2}(w^2(r+\tau) - 2w(xr+\mu\tau) + x^2 r + \mu^2\tau)\right) dw$$

$$= \frac{1}{\sqrt{2\pi}}\sqrt{\frac{r\tau}{r+\tau}} \exp\left(-\frac{1}{2}\left(\frac{r\tau}{r+\tau}\right)(x-\mu)^2\right) \int \sqrt{\frac{r+\tau}{2\pi}} \exp\left(-\tfrac{1}{2}(r+\tau)\left(w - \frac{xr+\mu\tau}{r+\tau}\right)^2\right) dw$$

$$= \frac{1}{\sqrt{2\pi}}\sqrt{\frac{r\tau}{r+\tau}} \exp\left(-\frac{1}{2}\left(\frac{r\tau}{r+\tau}\right)(x-\mu)^2\right)$$

which is the probability density function of normal distribution with mean μ and variance $(r+\tau)/r\tau$. From standard probability theory, it also derives that $\overline{c}_{ij}$ is normal with mean μ and variance $(r+\tau)/nr\tau$. ■

Using the lemma, it is possible to derive the following theoretical results:

Proposition 1 *The probability of strategic reaction increases when* τ_{ij} *decreases for* $n_{ijt} < n^*$*, with* $n^* > 1$*. Hence, the probability of strategic reaction to rival investment is positively related to the uncertainty surrounding expected cost when the number of rival investments is sufficiently small.*

Proof. See Appendix ■

Proposition 2 *The effect on the probability of strategic reaction of an increase in* r_{ij} *or* n_{ijt} *is negative.*

Proof. See Appendix. ■

The intuition behind the theoretical propositions is that an increase in precision τ_{ij} leads to more weight on μ_{ij} in the posterior mean of expected cost, which leads to a lower chance that $\pi_{ij} > \mu_{ijt}$. Hence, τ_{ij} is negatively related to the probability of strategic reaction for not too large values of n[7].

The effect of the precision parameter r_{ij} is instead always negative, i.e. an increase in uncertainty leads to an increase in the probability of investment through strategic reaction, so for a given $n_{ijt} < n^*$ both precision parameters work in the same direction.

As far as the parameter n_{ijt} is concerned, the effect is also negative, indicating that the conditional probability of investment is negatively related to the number of investment. The intuition is as follows. If the number of firms goes up, and there has not been any strategic reaction, the marginal change in the posterior mean of the observed production cost decreases. In other words, changes in the posterior mean, due to new cost observations and affecting the propensity to invest, are highest when it concerns the first observations of production cost. This is exactly what we mean by *oligopolistic* reaction: follow-the-leader investment is most likely when there are few rival firms that have invested. If the number of investors goes up, strategic reaction declines.

[7] So, for large values of n the effect of τ can be positive. The intuition behind this result is that for large n the posterior mean tends to the average observed cost. In that case, if $\pi_{ij} + \pi^f - \bar{c} > 0$, it follows from (2) that an increase in precision τ leads to a higher probability of strategic reaction. Since $E[\bar{c}] = \mu$, such a positive effect can only arise when $\pi_{ij} + \pi^f$ is close to μ_{ij}. If instead $\pi_{ij} + \pi^f$ is not sufficiently close to μ_{ij}, n^* is infinite, and the probability of strategic reaction increases when τ_{ij} decreases for all n.

For the empirical analysis of Bayesian learning, developed in the next section, the 'dual' approach may be more relevant. In the dual problem, instead of being uncertain about costs while knowing the revenues, the firm is uncertain about the revenues, while knowing its cost of producing abroad. So, a low cost firm will invest first and reveal its revenues to rival firms. If the revenue is higher than expected, rival firms will adjust expected revenues upward, which may trigger further investment.

3 Econometric approach

In order to test the predictions of the Bayesian learning from rival firms in an empirical study, we model the expected profit from FDI including the previously discussed variables related to Bayesian learning. Covariates for profitability included in X_{ijt} are standard gravity-type variables represented by $SIZE_{jt}$ (log of country size proxied by its population), $GDPPC_{jt}$ (log of gross domestic product per capita) and $DISTj$ (log of kilometric distance between the capital city of the host country and an average EU location). Further explanatory variables are the comparative advantage of the host country in terms of labor costs ($RELWAGE_{jt}$), and two industry-related variables, namely the average size of the industry ($INDSIZE_{it}$) and dummies for industries with high sunk costs ($HIGH_i$) and moderate sunk costs (MED_i), respectively. The dummies are constructed with a reference to Davies and Lyons (1996) who classified industries based on their NACE-codes as advertising and/or R&D intensive. The dummy for high sunk cost industries takes a value of 1 if the industry is both advertising and R&D intensive, while the dummy for moderate sunk costs is 1 if the industry is either advertising or R&D intensive (see Annex for a more detailed description of all variables).

In the theoretical model, the exogenous variables related to Bayesian learning are related to the uncertainty with which costs are observed and to the number n of early-mover information-revealing firms a potential investor observes in a period. Considering the dual approach, we can take uncertainty about revenues of the investing firms instead. Recalling Lemma 1, the unconditional probability of the distribution of costs or revenues (then relevant for the observed costs or revenues) is normal, with variance (uncertainty) depending monotonously on both precision parameters r and τ. Thus, we can proxy both r_{ij} and τ_{ij} through one variable ($INDUNC_{ij}$) which has an industry and a country-specific dimension.

In particular, $INDUNC$ is measured as the average coefficient of variation[8] of EBIT (earnings before interest and taxes) of a sample of firms currently operating in the countries and industries under consideration. The source is the AMADEUS dataset, provided by Bureau van Dijck, a consulting firm operating in Brussels, and containing balance sheet data of a sample of roughly 5,000,000 companies operating in Europe. Of the almost 180,000 companies recorded in the seven countries considered in our sample, we have restricted our analysis to the 32,083 firms for which data are available for at least four consecutive years in order to have a meaningful estimate of each firm's EBIT standard deviation. Hence, on average the EBIT coefficient of variation is calculated with 95 firms per observation.

A series of categorical dummies measure instead the amount of investment in the previous years (the parameter n). The categorical dummies measuring the evolution of foreign investors are L_{ijt}, M_{ijt}, H_{ijt}, and VH_{ijt}. They indicate respectively that in the previous year the first and/or second investment (L_{ijt}), the third, fourth or fifth investment (M_{ijt}), the sixth until tenth investment (H_{ijt}) or the eleventh or later (VH_{ijt}) investment took place in industry i of country j at time t. The interpretation of the investment dummies is very different. On one side of the extremes, L_{ijt} examines the impact of the first and second mover on later investment. Clearly, this variable is most relevant for oligopolistic reaction. On the other side of the extreme, VH_{ijt} shows the relevance of an increase in an already large number of firms in the industry. As such, the variable is likely to pick up agglomeration dynamics in the considered country/industry pair. All investment dummies also pick up a competition effect, which predicts a negative relation between rival entry in an industry and profitability of entry. The sign and significance of the investment dummies and the interactions with uncertainty will determine which effect dominates.

Nevertheless, for testing the explicit channel of OR through Bayesian learning, the interaction between L_{ijt} and $INDUNC_{ij}$ is the crucial variable. If the interaction term is not included, in fact, the measure of eventual oligopolistic reaction is entirely embodied in the coefficient for L_{ijt}. A positive and significant coefficient would be a necessary condition for detecting oligopolistic reaction (since we would have evidence of firms reacting to rivals' entry), but it would not convey any information on the channel through which the oligopolistic

[8]Note that the coefficient of variation, defined as the standard deviation over the mean, is dimensionless.

reaction takes place. If OR only takes place through Bayesian learning, instead, the theoretical model predicts that the interaction term ($L_{ijt} * INDUNC_{ij}$) should be positive and significant when both L_{ijt} and the interaction are included in the estimation, with the coefficient for L_{ijt} alone not significantly different from zero (since the impact of rivals' entry on the potential investor's expected return only takes place through the learning effect)[9].

The dependent variable in our study (y_{ijt}) is the number of foreign investments in sector i of a particular CEEC j at time t, as derived from the PECODB dataset. The Annex lists the 48 sectors and 7 CEECs that are considered in our study, while Table 1 presents the yearly distribution of the entrants per industry over the period 1990-1997. The first year is the one in which the investment opportunities were created by the start of the transition process, opportunities eventually exploited by first-mover multinationals. As the percentage of investors is generally non-zero after the first entry, Table 1 gives some preliminary evidence consistent with oligopolistic reaction FDI.

In order to avoid a simultaneity bias, we have lagged all the covariates (not only the investment dummies) one year[10]. Note that, through the use of categorical dummies for modelling previous investments, we do not introduce serial correlation in the error term, a bias which would have required a dynamic discrete choice panel data model design, the distribution of which is however still under study by the theoretical literature[11].

[Table 1 about here]

Since the dependent variable is a count variable, the most basic assumption on its distribution is that it is Poisson distributed, hence with a density function which equals

$$f(y_{ijt} \mid \lambda_{ijt}) = \frac{\exp(-\lambda_{ijt})\lambda_{ijt}^{y_{ijt}}}{y_{ijt}!} \tag{4}$$

[9] This can be best illustrated by examining the case of no Bayesian learning, i.e. the case in which uncertainty about production cost is zero. If only the channel of OR through Bayesian learning is considered, in this case the total effect of foreign entry by the first/second investor on the expected profitability of the potential investor should be zero. Since the interaction term ($L_{ijt} * INDUNC_{ij}$) is zero, there is no effect of L_{ijt} only if the coefficient for L_{ijt} is also zero.

[10] The economic rationale for lagging the covariates is also related to the evidence of the so-called "time to build" period elapsing between the actual timing of investment and the decision to invest.

[11] See Honoré and Kyriazidou (2000) for a reference to this class of models.

Parameter λ_{ijt} represents the mean and depends on covariates by the function $\ln(\lambda_{ijt}) = X'_{ijt}\boldsymbol{\delta}$, where $\boldsymbol{\delta}$ is a parameter vector.

However, a key assumption of the Poisson distribution is that the variance is equal to the mean. Such an assumption is likely to be violated when dealing with our sample, since it is well known that count data typically show overdispersion (i.e. variance greater than the mean) when there is either unobserved heterogeneity and/or 'positive contagion' (one event increases the likelihood of another), two features which are likely to arise given the economic nature of our data. In the case of overdispersion, the Poisson estimates are inefficient, with standard errors biased downwards.

As a result, in line with Hausman et al. (1984) we generalize the Poisson model by introducing an individual unobserved effect in the conditional mean of the Poisson distribution. For mathematical convenience a gamma distribution with parameters ϑ_{ijt} and $1/\alpha$ is assumed for the conditional mean, with ϑ_{ijt} now a function of covariates so that $\ln(\vartheta_{ijt}) = X'_{ijt}\boldsymbol{\delta}$. The resulting distribution of the dependent variable is a (panel) negative binomial (NB1 according to the specification in Cameron and Trivedi, 1998), the density of which equals

$$f(y_{ijt} \mid \vartheta_{ijt}, \alpha) = \frac{\Gamma(\vartheta_{ijt} + y_{ijt})}{\Gamma(y_{ijt} + 1)\Gamma(\vartheta_{ijt})} \left(\frac{\alpha}{1+\alpha}\right)^{y_{ijt}} \left(\frac{1}{1+\alpha}\right)^{\vartheta_{ijt}} \tag{5}$$

where $\Gamma(.)$ is a standard gamma distribution and $\alpha > 0$. The main advantage of the negative binomial model over a standard Poisson model is that the former allows for a different mean and variance. More specifically, in Equation (5) the ratio of variance and mean can be calculated as $1 + \alpha$. So the parameter α can be interpreted as a dispersion parameter. The negative binomial distribution thus becomes a Poisson distribution as $\alpha \downarrow 0$.

Since we are dealing with an industry-, country- and time-specific dimension in count data where observed heterogeneity or positive contagion are not unlikely, it matters how both the panel nature of the conditional mean and the overdispersion parameter α are modelled, and hence we have opted for several different model specifications in order to derive robust results.

As a benchmark for the econometric analysis, it is convenient to start from the standard Poisson model reported in (4), thus ignoring the panel dimension in the data (Model 1). Next, a gamma distribution with parameters ϑ_{ijt} and $1/\alpha$ is assumed for each conditional mean λ_{ijt}, leading to the standard negative binomial model (5), with overdispersion held constant across all industries and countries pairs (Model 2). Model 3 and 4 use the same density function of Model 2, but tackle the three-dimensional nature of the conditional mean considering industry- and both industry- and country-fixed effects in ϑ_{ijt}, respectively.

As a next step, we explicitly deal with the panel dimension of our data, in which we control for the industry-specific nature of the conditional mean: a gamma distribution is assumed for each industry mean in a given year (λ_{it})[12] yielding our Model 5. In Model 6, we consider an industry-specific overdispersion parameter (α_i), conditioning the joint probability of the counts for each industry i on the sum jt of the counts for the group. Note that since the mean of the $\Gamma(\vartheta_{ijt}, 1/\alpha_i)$ distribution equals ϑ_{ijt}/α_i, in this case the industry-specific overdispersion parameter also acts as an industry-fixed effect in the mean, along the same lines of Model 3, but this time taking into account the panel nature of the data. Finally, as a robustness check, we estimate the same negative binomial panel model allowing the overdispersion parameter to vary randomly across groups. More specifically, in Model 7 it is assumed that a monotone transformation of the overdispersion parameter, $(1/1 + \alpha_i)$, is drawn from a beta distribution with parameters ν_1 and ν_2, allowing for a more parsimonious way to account for heterogeneity in the overdispersion parameter[13].

The following scheme summarizes the different model specifications employed in the analysis.

Model 1	$y_{ijt} \sim Poisson(\lambda_{ijt})$
Model 2	$\lambda_{ijt} \sim \Gamma(\vartheta_{ijt}, 1/\alpha)$
Model 3	$\lambda_{ijt} \sim \Gamma(\vartheta_{ijt}, 1/\alpha)$ with i-fixed effects in ϑ_{ijt}
Model 4	$\lambda_{ijt} \sim \Gamma(\vartheta_{ijt}, 1/\alpha)$ with i- and j-fixed effects in ϑ_{ijt}
Model 5	$\lambda_{it} \sim \Gamma(\vartheta_{ijt}, 1/\alpha)$
Model 6	$\lambda_{it} \sim \Gamma(\vartheta_{ijt}, 1/\alpha_i)$
Model 7	$\lambda_{it} \sim \Gamma(\vartheta_{ijt}, 1/\alpha_i)$ with $(1/1 + \alpha_i) \sim Beta(\nu_1, \nu_2)$

[12]In other words, the industry mean is assumed to be constant across all countries. This assumption is released in Section 5 of the paper.

[13]In this last case the mean of the beta distribution is known to be $\nu1/(\nu1+\ \nu2)$. The assumption of a beta distribution leads to a tractable joint probability distribution (see Hausman et al., 1984), so maximum likelihood estimation of the parameters is straightforward.

4 Results

Table 2 shows the results for the pooled specifications of the estimation (i.e. Models 1 to 4 in the previous scheme). The first set of control variables have the expected sign and are overall significant. More specifically, the 'gravity variables' measuring population size and GDP per capita are positive while the variable measuring distance is negative. These results show that horizontal (market-seeking) investment explains a significant portion of the total number of incoming investment. Nevertheless, also the relative wage variable is negative and significant, indicating that vertical investment where firms outsource activities to the CEECs is also important[14]. The industry size variable is positive, although not always significant, showing that investment is more likely in sectors that are relatively large. Without taking into account the OR channel, uncertainty alone is negative, although not strongly significant across the different model specifications, in line with the finding in the literature on uncertainty and FDI[15]. Only when the regression takes into account both sector and country fixed effects, some of the country variables lose their significance (Model 4a in Table 2).

Looking at the second set of variables in Table 2, there is strong evidence for oligopolistic reaction since the previously discussed conditions on the parameter for L_{ijt} and its interaction with uncertainty are met for the different model specifications. Leaving out the interaction between uncertainty and total early investment in the previous year (all models labelled 'a' in Table 2), we find a positive and significant effect of the latter variable, and hence evidence that firms react to rivals' entry. However, when we include the interaction with uncertainty (all models labelled 'b' in Table 2), as predicted by our theoretical model the dummies measuring early investment tend to be less significant, in particular when industry- and country-fixed effects are included in the estimation (Models 3b and 4b in Table 2). At the same time, the interaction variable in these latter cases tends to become positive and significant, and hence oligopolistic reaction can only be attributed to the Bayesian learning explanation that we put forward. Moreover, oligopolistic reaction is robust with respect to

[14] Alessandrini (2000) among others reports evidence that both market-seeking and efficiency-seeking strategies have been pursued by MNEs investing in the CEECs.

[15] See Brunetti and Weder (1998) for an empirical analysis.

industry- and country-fixed effects (Models 3 and 4) which, when included, yield the best model specification[16].

The results also show that the dynamic effects of agglomeration outweigh the competition effect if the threshold of ten previous investments is crossed (the VH_{ijt} dummy takes value 1). Since it is well-known that economies of scale are one of the sources of agglomeration benefits, as a robustness check the VH_{ijt} variable is interacted with a dummy variable ES that takes the value of 1 in industries where economies of scale are important (Pavitt, 1984)[17]. The interaction has, as expected, a positive sign, thus providing some evidence of agglomeration effects; however, it is significant only when country- and industry-fixed effects are not considered, as it can be seen comparing Models 1 and 2 with Models 3 and 4 in Table 2.

The interaction between uncertainty and VH_{ijt} is negative, a result not in contrast with the combined predictions of Propositions 1 and 2. However, an explanation might also be linked to the possibility that agglomeration effects are higher in industries where firms tend to be more similar. A higher uncertainty might hence be related to a lower degree of similarity between firms, and hence induce a negative sign in the interaction effect.

In terms of model design, the benchmark Model 1 in Table 2 relies on some restrictive assumptions. In particular, as discussed earlier, the Poisson distribution (Model 1a and 1b) is very restrictive in the sense that it imposes the mean to be equal to the variance. Models 2 to 4 show the results for several specifications of the negative binomial model, which generalises the Poisson distribution allowing for overdispersion. The estimates of the overdispersion parameter reported in the last row of Table 2 show that the hypothesis of no overdispersion is clearly rejected. Under these more flexible model specifications, our main findings remain however valid, illustrating their robustness.

[Table 2 about here]

[16]The specification tests reported in Table 2 are LR specification tests, all nested starting from Model 1. Essentially, in Model 2 the restriction that the overdispersion parameter is zero is rejected. In Model 3 and 4, together with the restriction on the overdispersion parameter, the hypothesis of joint industry (Model 3) and country/industry (Model 4) fixed effects equal to zero is also rejected.

[17]See the data Appendix for the classification of industries that exhibit economies of scale.

As a further step, in Table 3 we have explicitely modelled the panel nature of our data. The first columns (Model 5) show the results for the regression with a constant overdispersion parameter across groups. As discussed in the previous section, the main difference with Model 2 is that the latter considers random effects for each observation ijt while Model 5 estimates random effects for industries it only. The previous result on oligopolistic reaction remains valid under this specification. Model 6 in Table 3 shows the results for the regression with industry-fixed effects in the dispersion parameter. As discussed earlier, Model 3 (random effects for each observation ijt plus industry-fixed effects) and Model 6 (random effects for industries it) are very close in structure. However, in Model 6 we also explicitly control for the panel nature of the overdispersion parameter through 48 industry-specific dispersion parameters α_i rather than the constant α used in Model 3. Model 6 equally passes the parameter tests and yields a higher likelihood than Model 3. Finally, Model 7 reports the specification where dispersion in each sector is randomly drawn from a beta distribution. Both Models 6 and 7 perform significantly better than the panel specification with a constant dispersion reported in Model 5. Still, the main results with respect to oligopolistic reaction and the control variables are hardly affected by this specification.

[Table 3 about here]

5 An extension: country-specific heterogeneity

In Table 3 we have reported the results for model specifications in which the panel group structure of the data was considered only across industries i, ignoring possible biases arising from country heterogeneity. A straightforward way to control for country heterogeneity is to maintain the industry-specific structure of Table 3 introducing country-specific dummies. A possible additional set of such dummies, convenient for our analysis[18], considers the fact that information about production costs may also be revealed by firms that invest in the same industry i, but in a country $s \neq j$. Investment dummies CL_{ijt}, CM_{ijt}, CH_{ijt}, CVH_{ijt}

[18] Our profit-related covariates already being country-specific, country-fixed effects are highly correlated with the former set of variables, and thus their introduction would generate multicollinearity in the model specification.

therefore indicate, respectively, that in the previous year the first and/or second investment (CL_{ijt}), the third, fourth or fifth investment (CM_{ijt}), the sixth until tenth investment (CH_{ijt}) or the eleventh or later (CVH_{ijt}) investment took place in the same industry i but in another country $s \neq j$ at time t.

Table 4 presents the results of the same panel estimations reported in Table 3 enriched with the dummies modelling country-specific heterogeneity. Our main findings for both the control variables and the oligopolistic reaction effect remain valid. In fact, when controlling for information spillovers from investment flowing into other countries, the previously discussed conditions on the parameter for L_{ijt} and its interaction with uncertainty are also satisfied in these model specifications, albeit with a smaller degree of significance. Once the channel of Bayesian learning from other countries is duly considered in explaining follow-up investments (Models 'b' in Table 4), uncertainty alone in a given country j ($INDUNC_{ij}$) also turns out to be a significant, negative determinant of FDI. The reason is that the interaction terms of the investment dummies and uncertainty are broadly positive, so uncertainty negatively affects investment if there was no prior investment. In a sense, uncertainty affects investment negatively, through the effects found in the literature[19], and through Bayesian learning, this time with an overall positive effect. Once we control for the latter interaction, a negative significant signs appears in the estimates of uncertainty alone.

As far as the cross-country investment dummies are concerned, we have some evidence of FDI from rival firms acting as strategic substitutes rather than complements. In two of the model specifications where the OR channel is not considered (Models 5a' and 6a'), it can be seen that a higher number of previous investments in other countries $s \neq j$ (dummies CH and CVH) affects negatively and significatively new FDI undertakings in country j, thus suggesting a tendency toward industry concentration / geographical specialization by MNEs. Finally, the positive and significant interaction between CL and *indunc* in Models 6 and 7 of Table 4 provides some evidence of learning from rivals that established a first or second investment in a given industry in a country different from the host one. Oligopolistic reaction to investments in other CEECs however is not a robust finding, being it affected by

[19]In general three channels through which uncertainty can affect investment can be identified: the option theory of irreversible investment, financing constraints and risk-aversion. For a short discussion of this literature see Ghosal and Loungani (2000).

the negative effect of competition for investment within the CEECs.

[Table 4 about here]

6 Conclusion

Paying tribute to the original intuition by Knickerbocker (1973), and capitalising on the recent attempts of formally supporting his result through a theoretical model, the paper shows that, alongside more traditional determinants of FDI, oligopolistic reaction driven by a formal process of Bayesian learning by rival firms also plays a significant role in driving MNEs' decisions to invest abroad. This result is robust with respect to different model specifications which control for both industry and country heterogeneity.

Two future lines of research are evident to us. First of all, the long studied issue of strategic substituability or complementarity of FDI might be worth another closer look. In our paper, strategic substitues FDI seems to arise only after a certain threshold in the number of rivals is reached, and only with respect to FDI undertaken in countries different than the one in which the considered investment is taking place. When previous investments in the same country are considered, instead, agglomeration effects and Bayesian learning oligopolistic reaction leading to FDI complementarity seem to prevail. As a result, the effects of FDI substitution or complementarity seem to be a function of the geographical space in which rivals are considered.

Second, it is obvious that the use of categorical dummies for modelling previous investments suffers from some potential shortcomings, threshold effects being the most evident ones. Therefore, the results of this paper should be validated as soon as the new econometric techniques on dynamic discrete panel data models move from the frontier of teorethical research to more routinely methodological tools.

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Appendix

(Proof of Proposition 1). First note that firm f invests at time t when revenues exceeds expected cost, so when $\pi_{ijt} + \pi^f > \mu_{ijt}$. If firm f has not invested up to time $t-1$, it must be true that $\pi_{ijt} + \pi^f < \mu_{ijt-1}$. Given that firm f also did not invest at the beginning of the period, it must also hold that $\pi_{ij} + \pi^f < \mu_{ij}$.

Dropping the industry and country index, the first order derivative of (3) with respect to τ is

$$\frac{\partial p^f|\overline{c}}{\partial \tau} = \varphi\left((\pi+\pi^f)\sqrt{\tau+nr} - \frac{\mu\tau+nr\overline{c}}{\sqrt{\tau+nr}}\right)\left(\frac{(\pi+\pi^f)}{2\sqrt{\tau+nr}} - \frac{\mu\sqrt{\tau+nr}-(\mu\tau+nr\overline{c})/2\sqrt{\tau+nr}}{\tau+nr}\right)$$
$$= \varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\overline{c}}{\sqrt{\tau+nr}}\right)\left(\frac{\pi+\pi^f-2\mu+\mu\tau/(\tau+nr)}{2\sqrt{\tau+nr}} + \frac{nr}{2(\tau+nr)\sqrt{\tau+nr}}\overline{c}\right)$$
$$= \varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\overline{c}}{\sqrt{\tau+nr}}\right)(A+B\overline{c})$$

Using Lemma (1) then the unconditional derivative can be derived as

$$\frac{\partial p^f}{\partial \tau} = \int \frac{\partial p^f|\overline{c}}{\partial \tau}\sqrt{\frac{nr\tau}{r+\tau}}\varphi\left(\frac{(\overline{c}-\mu)\sqrt{nr\tau}}{\sqrt{r+\tau}}\right)d\overline{c}$$
$$= \int (A+B\overline{c})\sqrt{\frac{nr\tau}{r+\tau}}\varphi\left(\frac{(\overline{c}-\mu)\sqrt{nr\tau}}{\sqrt{r+\tau}}\right)\varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\overline{c}}{\sqrt{\tau+nr}}\right)d\overline{c}$$
$$= \int \frac{(A+B\overline{c})}{2\pi}\sqrt{\frac{nr\tau}{r+\tau}}\exp\left(-\frac{1}{2}\left\{\overline{c}^2\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right) - 2\overline{c}\left(\frac{\mu nr\tau}{r+\tau}+\frac{nr\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)+D\right\}\right)$$
$$= \int F(A+B\overline{c})\exp\left(-\frac{1}{2}\left\{\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right)\left(\overline{c}-\left(\frac{\mu nr\tau}{r+\tau}+\frac{nr\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right)\right)^2\right\}\right)$$
$$= F\left(A+B\left(\frac{\mu\tau}{r+\tau}+\frac{\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= F\left(\frac{\pi+\pi^f-2\mu+\mu\tau/(\tau+nr)}{2\sqrt{\tau+nr}}+\frac{nr}{2(\tau+nr)\sqrt{\tau+nr}}\left(\frac{\mu\tau}{r+\tau}+\frac{\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= G\left(\frac{\pi+\pi^f-\mu}{2}+\frac{-\mu+\mu\tau/(\tau+nr)}{2}+\frac{nr}{2(\tau+nr)}\left(\frac{\mu\tau}{r+\tau}+\frac{\tau(\pi+\pi^f-\mu)+nr(\pi+\pi^f)}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= G\left(\frac{\pi+\pi^f-\mu}{2}+\frac{nr}{2(\tau+nr)}\left((\pi+\pi^f-\mu)+\frac{\mu\tau}{r+\tau}-\frac{\mu\tau}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$

where F and G are positive constants. Since $(\pi+\pi^f-\mu)<0$, the expression is negative for $n=1$. For $n>1$, the sign depends on the parameters and can be positive for n large enough. Therefore, there exists $n^*>1$, possibly infinite, such that the effect is negative for $n<n^*$. QED ■

(Proof of Proposition 2). Given (3), its conditional derivative with respect to r (again dropping the country and industry subscripts) can be written as

$$\frac{\partial p^f|\bar{c}}{\partial r} = \varphi\left((\pi+\pi^f)\sqrt{\tau+nr} - \frac{\mu\tau+nr\bar{c}}{\sqrt{\tau+nr}}\right)\left(\frac{(\pi+\pi^f)n}{2\sqrt{\tau+nr}} - \frac{n\bar{c}\sqrt{\tau+nr}-n(\mu\tau+nr\bar{c})/2\sqrt{\tau+nr}}{\tau+nr}\right)$$
$$= \varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\bar{c}}{\sqrt{\tau+nr}}\right)\left(\frac{\pi+\pi^f+\mu\tau/(\tau+nr)}{2\sqrt{\tau+nr}} + \frac{nr-2(\tau+nr)}{2(\tau+nr)\sqrt{\tau+nr}}\bar{c}\right)n$$
$$= \varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\bar{c}}{\sqrt{\tau+nr}}\right)(A+B\bar{c})\,n$$

Taking the expectation with respect to the average cost gives

$$\frac{\partial p^f}{\partial r} = \int \frac{\partial p^f|\bar{c}}{\partial r}\sqrt{\frac{nr\tau}{r+\tau}}\varphi\left(\frac{(\bar{c}-\mu)\sqrt{nr\tau}}{\sqrt{r+\tau}}\right)d\bar{c}$$
$$= \int (A+B\bar{c})\,n\sqrt{\frac{nr\tau}{r+\tau}}\varphi\left(\frac{(\bar{c}-\mu)\sqrt{nr\tau}}{\sqrt{r+\tau}}\right)\varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\bar{c}}{\sqrt{\tau+nr}}\right)d\bar{c}$$
$$= \int \frac{(A+B\bar{c})}{2\pi}\sqrt{\frac{nr\tau}{r+\tau}}\exp\left(-\frac{1}{2}\left\{\bar{c}^2\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right) - 2\bar{c}\left(\frac{\mu nr\tau}{r+\tau}+\frac{nr\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)+D\right\}\right)n$$
$$= \int F\,(A+B\bar{c})\exp\left(-\frac{1}{2}\left\{\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right)\left(\bar{c}-\left(\frac{\mu nr\tau}{r+\tau}+\frac{nr\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{nr\tau}{r+\tau}+\frac{n^2r^2}{\tau+nr}\right)\right)^2\right\}\right)$$
$$= F\left(A+B\left(\frac{\mu\tau}{r+\tau}+\frac{\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= F\left(\frac{\pi+\pi^f+\mu\tau/(\tau+nr)}{2\sqrt{\tau+nr}}+\frac{nr-2(\tau+nr)}{2(\tau+nr)\sqrt{\tau+nr}}\left(\frac{\mu\tau}{r+\tau}+\frac{\left[(\pi+\pi^f)(\tau+nr)-\mu\tau\right]}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= G\left(\frac{\pi+\pi^f-\mu}{2}+\frac{\mu}{2}+\frac{\mu\tau}{2(\tau+nr)}+\frac{nr-2(\tau+nr)}{2(\tau+nr)}\left(\frac{\mu\tau}{r+\tau}+\frac{\tau(\pi+\pi^f-\mu)+nr(\pi+\pi^f)}{\tau+nr}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= G\left(\frac{\pi+\pi^f-\mu}{2}-\frac{nr+2\tau}{2(\tau+nr)}\left\{(\pi+\pi^f-\mu)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right\}\right)$$
$$= G\left(\frac{\pi+\pi^f-\mu}{2}\left\{1-\frac{nr+2\tau}{2(\tau+nr)}/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right\}\right)$$
$$= -H\left(1-\frac{nr+2\tau}{2(\tau+nr)}/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= -H\left(\left(\frac{\tau}{r+\tau}+\frac{2nr}{2(\tau+nr)}-\frac{nr+2\tau}{2(\tau+nr)}\right)/\left(\frac{\tau}{r+\tau}+\frac{nr}{\tau+nr}\right)\right)$$
$$= -I\left(\frac{\tau}{r+\tau}+\frac{nr-2\tau}{2(\tau+nr)}\right)$$
$$= -J\left(3nr\tau+nr^2-2r\tau\right)$$

where F, G, H, I and J are positive constants. So the last expression is negative when $3nr\tau+nr^2-2r\tau>0$, or $n>\frac{2\tau}{3\tau+r}$. Since $\frac{2\tau}{3\tau+r}<1$ and $n\geq 1$, the expression is negative.

Analogously, taking the conditional derivative of (3) with respect to n, we have that

$$\frac{\partial p^f|\bar{c}}{\partial n} = \varphi\left((\pi+\pi^f)\sqrt{\tau+nr} - \frac{\mu\tau+nr\bar{c}}{\sqrt{\tau+nr}}\right)\left(\frac{(\pi+\pi^f)r}{2\sqrt{\tau+nr}} - \frac{r\bar{c}\sqrt{\tau+nr}-r(\mu\tau+nr\bar{c})/2\sqrt{\tau+nr}}{\tau+nr}\right)$$
$$= \varphi\left(\frac{(\pi+\pi^f)(\tau+nr)-\mu\tau-nr\bar{c}}{\sqrt{\tau+nr}}\right)\left(\frac{\pi+\pi^f+\mu\tau/(\tau+nr)}{2\sqrt{\tau+nr}} + \frac{nr-2(\tau+nr)}{2(\tau+nr)\sqrt{\tau+nr}}\bar{c}\right)r$$

So, the condition for a negative sign of the unconditional derivative of p^f with respect to n is exactly equal as for the derivative with respect to r. Hence, for $n \geq 1$ we have that both $\frac{\partial p^f}{\partial r} < 0$ and $\frac{\partial p^f}{\partial n} < 0$. QED ■

Table 1. Yearly shares of entrants in the period 1990-1997

(percentage over total FDI recorded in the CEECs – industry breakdown)

Industry	*1990*	*1991*	*1992*	*1993*	*1994*	*1995*	*1996*	*1997*
10.14	4.5	6.1	31.8	24.2	10.6	10.6	4.5	7.6
151.152	8.3	16.7	37.5	20.8	8.3	0.0	8.3	0.0
153.55	0.0	10.5	17.4	19.8	17.4	17.4	7.0	10.5
156	0.0	0.0	22.2	33.3	11.1	11.1	11.1	11.1
157	14.3	0.0	42.9	14.3	0.0	14.3	14.3	0.0
158	2.2	10.1	15.1	20.9	11.5	23.7	7.2	9.4
159	0.9	7.1	17.7	23.0	17.7	14.2	15.0	4.4
16	0.0	19.0	28.6	14.3	9.5	14.3	9.5	4.8
17	7.1	8.6	8.6	18.6	18.6	15.7	10.0	12.8
18	4.7	12.8	11.6	23.3	10.5	19.8	12.8	4.7
19	20.8	0.0	20.8	16.7	8.3	25.0	8.3	0.0
20	2.3	6.8	11.4	18.2	11.4	29.5	13.6	6.8
21	2.2	0.0	15.2	13.0	8.7	19.6	13.0	28.3
22	1.6	14.1	14.1	32.8	12.5	10.9	9.4	4.7
241.242	3.2	3.2	17.7	33.9	16.1	9.7	14.5	1.6
243.45	2.6	7.9	13.2	19.7	18.4	19.7	6.6	11.8
246.247	0.0	13.3	13.3	20.0	0.0	40.0	6.7	6.7
251	0.0	0.0	11.1	22.2	11.1	27.8	16.7	11.2
252.262	6.3	4.9	10.4	24.3	16.0	9.0	15.3	13.9
26	0.9	5.4	16.1	17.9	18.8	15.2	6.3	19.6
27	1.5	1.5	23.1	20.0	12.3	23.1	3.1	15.4
28	0.0	6.5	14.5	17.7	27.4	4.8	14.5	14.5
291	0.0	17.2	10.3	17.2	17.2	6.9	13.8	17.2
292	16.7	16.7	4.2	12.5	33.3	8.3	8.3	0.0
293	11.1	0.0	0.0	22.2	33.3	11.1	11.1	11.1
294.295	0.0	9.4	11.3	9.4	35.8	13.2	13.2	7.6
297	0.0	5.0	20.0	25.0	15.0	0.0	20.0	15.0
30	11.1	0.0	11.1	0.0	33.3	11.1	11.1	22.2
31	2.9	7.7	10.6	36.5	14.4	11.5	7.7	8.7
321	4.2	4.2	8.3	33.3	16.7	0.0	16.7	24.9
322.323	2.0	4.1	18.4	32.7	16.3	16.3	6.1	4.1
331.332	8.3	8.3	16.7	33.3	25.0	0.0	8.3	0.0
334.335	0.0	0.0	0.0	0.0	20.0	60.0	20.0	0.0
341	2.7	16.2	16.2	16.2	13.5	13.5	8.1	13.5
343	1.1	3.3	12.0	27.2	17.4	15.2	4.3	19.6
351	0.0	0.0	0.0	0.0	20.0	20.0	20.0	40.0
352.354	4.3	0.0	17.4	21.7	17.4	4.3	13.0	21.7
361.362	4.8	2.4	11.9	31.0	19.0	11.9	7.1	11.9
363.365	0.0	12.5	0.0	25.0	12.5	25.0	12.5	12.5
366	0.0	0.0	0.0	0.0	20.0	20.0	0.0	60.0
401.402	0.0	0.0	4.1	10.8	14.9	37.8	12.2	20.3
45	7.4	10.6	14.9	25.5	10.6	16.0	6.4	8.5
55	3.2	8.1	11.3	37.1	12.9	19.4	4.8	3.2
642	1.6	8.1	8.1	27.4	6.5	16.1	21.0	11.3
65.66	3.0	10.5	10.5	10.2	19.5	18.4	16.5	11.3
72	0.0	10.0	10.0	20.0	20.0	0.0	30.0	10.0
73	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
92	0.0	3.3	6.7	13.3	30.0	6.7	30.0	10.0

Source: author's calculations based on PECODB dataset

Table 2. Baseline (pooled) models

	Poisson		Negative Binomial					
	(1a)	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**	**(4a)**	**(4b)**
const	.68 (.17)	-.73 (-.18)	6.89 (1.31)	5.25 (1.00)	-14.9** (-2.78)	-16.5 (-3.09)	-155.9* (-1.93)	-127.2 (-1.57)
size	.54** (13.7)	.52** (13.2)	.50** (9.59)	.49** (9.36)	.84** (15.0)	.83** (14.8)	17.6* (1.90)	14.1 (1.52)
gdppc	.43* (1.78)	.53** (2.20)	.01 (.05)	.14 (.45)	1.54** (4.60)	1.67** (5.00)	-.75 (-.89)	-.29 (-.34)
relwage	-.64** (-3.68)	-.71** (-4.05)	-.36* (-1.72)	-.45** (-2.11)	-1.05** (-4.77)	-1.14** (-5.15)	-.20 (-.30)	-.47 (-.70)
dist	-1.27** (-4.05)	-1.16** (-3.67)	-1.67** (-3.85)	-1.54** (-3.54)	-.64 (-1.52)	-.51 (-1.22)	-	-
indsize	.08** (6.96)	.07** (6.46)	.06** (3.92)	.06** (3.68)	.06 (1.41)	.06 (1.48)	.06 (1.37)	.06 (1.38)
indunc	-.04* (-1.74)	-.03 (-.66)	-.06** (-1.96)	-.13* (-1.76)	-.01 (-.43)	-.11 (-1.45)	-.03 (-.89)	-.12 (-1.46)
Med	-.07 (-1.64)	-.05 (-1.19)	-.08 (-1.21)	-.06 (-.97)	-	-	-	-
High	-.14** (-2.07)	-.15** (-2.27)	-.11 (-1.26)	-.12 (-1.37)	-	-	-	-
L	1.05** (13.6)	.87** (4.89)	.94** (9.32)	.60** (2.61)	.46** (4.40)	-.03 (-.12)	.40** (3.81)	-.05 (-.22)
M	.58** (8.15)	.68** (4.24)	.57** (5.49)	.71** (3.14)	.21** (2.08)	.39* (1.73)	.19* (1.86)	.39* (1.73)
H	.23** (3.15)	.13 (.73)	.27** (2.52)	.01 (.06)	.01 (.09)	-.13 (-.53)	-.05 (-.55)	-.22 (-.90)
VH	.51** (6.39)	1.29** (6.53)	.47** (3.99)	1.25** (4.55)	.08 (.64)	.85** (3.06)	.07 (.63)	.85** (3.08)
*VH*ES*	.25** (3.26)	.25** (3.18)	.23* (1.95)	.24** (2.02)	.05 (.39)	.03 (.23)	.06 (.47)	.04 (.33)
*L*indunc*	-	.08 (1.16)	-	.16 (1.60)	-	.24** (2.30)	-	.22** (2.14)
*M*indunc*	-	-.04 (-.69)	-	-.07 (-.73)	-	-.09 (-.95)	-	-.10 (-1.05)
*H*indunc*	-	.04 (.60)	-	.11 (1.11)	-	.06 (.59)	-	.07 (.72)
*VH*indunc*	-	-.36** (-4.29)	-	-.36** (-3.14)	-	-.35** (-3.09)	-	-.36** (-3.11)
Time dummies	*261.2***	*271.9***	*102.7***	*108.9***	*116.1***	*123.2***	*47.1***	*49.4***
Industry dummies	-	-	-	-	*288.1***	*290.1***	*306.3***	*306.4***
Country dummies	-	-	-	-	-	-	*36.7***	*34.4***
Overdispersion alpha	-	-	1.39** (.12)	1.37** (.11)	.95** (.09)	.93** (.09)	.89** (.09)	.87** (.09)
Log likelihood	-2727.6	-2713.3	-2393.2	-2386.8	-2240.4	-2232.5	-2222.9	-2215.4
N. of obs.	2208	2208	2208	2208	2208	2208	2208	2208
Specification test [a]	-	-	668.8**	652.9**	336.1**	326.2**	300.2**	293.8**

Note: T-statistics in parentheses (standard deviation for the overdispersion parameter). For time, industry and country dummies the joint test of significance is reported.
** significant at the 5 per cent level or more; * significant at the 10 per cent level.

[a] χ^2 *test statistic of LR specification test. Model 1 is the benchmark.*

Table 3. Negative binomial panel models

	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)
const	-19.8** (-4.74)	-21.1** (-5.03)	-13.4** (-2.45)	-14.9** (-2.71)	-10.1* (-1.85)	-11.5** (-2.12)
size	.83** (19.1)	.81** (18.7)	.82** (14.4)	.81** (14.3)	.77** (13.5)	.76** (13.4)
gdppc	1.86** (7.00)	1.96** (7.37)	1.51** (4.44)	1.63** (4.80)	1.26** (3.71)	1.38** (4.09)
relwage	-1.29** (-6.96)	-1.36** (-7.29)	-1.07** (-4.79)	-1.15** (-5.14)	-.94** (-4.25)	-1.03** (-4.61)
dist	-.23 (-.73)	-.12 (-.39)	-.73* (-1.69)	-.61 (-1.41)	-.88** (-2.03)	-.75* (-1.75)
indsize	.05** (2.06)	.06** (2.10)	.01 (.13)	.01 (.06)	.03 (.94)	.02 (.84)
indunc	-.01 (-.06)	-.04 (-.73)	-.02 (-.72)	-.12 (-1.51)	-.03 (-.80)	-.13 (-1.61)
Med	-.16 (-.67)	-.14 (-.60)	.16 (.75)	.13 (.61)	-.03 (-.20)	-.04 (-.28)
High	-.12 (-.39)	-.15 (-.48)	-.41 (-1.57)	-.36 (-1.36)	-.23 (-1.12)	-.21 (-1.01)
L	.62** (7.51)	.26 (1.42)	.49** (4.74)	.06 (.26)	.59** (5.58)	.14 (.59)
M	.22** (2.98)	.36** (2.12)	.19* (1.87)	.37 (1.63)	.26* (2.52)	.44* (1.95)
H	.01 (.07)	-.04 (.27)	.02 (.22)	-.20 (-.82)	.06 (.63)	-.16 (-.64)
VH	.11 (1.19)	.85** (4.05)	.06 (.53)	.85** (2.94)	.12 (.98)	.90** (3.17)
*VH*ES*	.03 (.32)	.01 (.07)	.02 (.16)	.01 (.09)	.04 (.28)	.03 (.23)
*L*indunc*	-	.17** (2.15)	-	.21** (2.01)	-	.22** (2.10)
*M*indunc*	-	-.06 (-.97)	-	-.09 (-.93)	-	-.09 (-.95)
*H*indunc*	-	.02 (.28)	-	.10 (.98)	-	.10 (.98)
*VH*indunc*	-	-.34** (-3.91)	-	-.36** (-3.01)	-	-.36** (-3.06)
Time dummies	*237.0***	*245.5***	*111.9***	*117.7***	*110.2***	*116.4***
Overdispersion alpha	.59** (.12)	.58** (.12)	-	-	-	-
ν_1	-	-	-	-	4.38** (1.06)	4.46** (1.08)
ν_2	-	-	-	-	2.76** (.69)	2.76** (.69)
Industry-specific α_i	No	No	Yes	Yes	No	No
Log likelihood	-2506.9	-2494.0	-2088.3	-2081.7	-2312.8	-2305.9
N. of obs.	2208	2208	2208	2208	2208	2208
Goodness of fit test [a]	441.3**	438. 5**	1278.5**	1263.2**	829.5**	814.7**

Note: T-statistics in parentheses (standard deviation for the overdispersion parameters). For time dummies the joint test of significance is reported.
** significant at the 5 per cent level or more; * significant at the 10 per cent level.

[a] χ^2 *test statistic of LR specification test. Model 1 is the benchmark.*

Table 4. Negative binomial panel models controlling for country heterogeneity

	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)
Const	-19.5**	-20.6**	-12.3**	-13.9**	-10.0*	-11.6**
	(-4.64)	(-4.88)	(-2.23)	(-2.51)	(-1.83)	(-2.12)
size	.83**	.82**	.81**	.81**	.76**	.76**
	(19.0)	(18.8)	(14.2)	(14.2)	(13.3)	(13.4)
Gdppc	1.84**	1.97**	1.46**	1.63**	1.23**	1.40**
	(6.91)	(7.35)	(4.25)	(4.71)	(3.63)	(4.10)
Relwage	-1.29**	-1.37**	-1.05**	-1.15**	-.93**	-1.03**
	(-6.94)	(-7.28)	(-4.70)	(-5.10)	(-4.18)	(-4.58)
dist	-.27	-.14	-.81*	-.64	-.88**	-.72*
	(-.83)	(-.45)	(-1.87)	(-1.47)	(-2.05)	(-1.66)
Indsize	.06**	.05**	.01	.01	.03	.03
	(2.03)	(1.98)	(.24)	(.10)	(1.07)	(.92)
Indunc	.01	-.28**	-.03	-.42**	-.03	-.40**
	(.08)	(-1.96)	(-.73)	(-2.35)	(-.83)	(-2.28)
Med	-.20	-.18	.13	.09	-.04	-.05
	(-.77)	(-.71)	(.59)	(.44)	(-.25)	(-.33)
High	-.19	-.22	-.54	-.49*	-.22	-.21
	(-.55)	(-.64)	(-2.03)**	(-1.84)	(-1.02)	(-.99)
L	.61**	.30	.49**	.10	.59**	.18
	(7.33)	(1.59)	(4.66)	(.40)	(5.55)	(.73)
M	.19**	.31*	.18*	.29	.26*	.39*
	(2.55)	(1.82)	(1.74)	(1.30)	(2.48)	(1.74)
H	.03	.02	.04	-.18	.09	-.14
	(.42)	(.01)	(.44)	(-.72)	(.84)	(-.56)
VH	.09	.81**	.03	.80**	.14	.90**
	(1.01)	(3.86)	(.25)	(2.76)	(1.05)	(3.17)
*VH*ES*	.01	-.01	.04	.02	.03	.01
	(.07)	(.13)	(.26)	(.17)	(.17)	(.06)
*L*indunc*	-	.15*	-	.19*	-	.19*
		(1.83)		(1.70)		(1.77)
*M*indunc*	-	-.06	-	-.06	-	-.07
		(-.88)		(-.64)		(-.75)
*H*indunc*	-	.01	-	.09	-	.09
		(.01)		(.91)		(.92)
*VH*indunc*	-	-.33**	-	-.36**	-	-.36**
		(-3.83)		(-3.00)		(-3.05)
CL	.07	-.42	-.09	-.89**	.15	-.54
	(.49)	(-1.16)	(-.54)	(-2.02)	(.78)	(-1.24)
CM	.15	.10	.15	.16	.26*	.24
	(1.36)	(.38)	(1.02)	(.48)	(1.77)	(.70)
CH	-.23**	-.09	-.28**	.05	-.14	.13
	(-2.44)	(-.41)	(-2.26)	(.17)	(-1.13)	(.46)
CVH	-.22**	-.37*	-.24*	-.39	-.06	-.16
	(-2.14)	(-1.89)	(-1.87)	(-1.54)	(-.46)	(-.66)
*CVH*ES*	.16	.15	.08	.09	.04	.05
	(1.51)	(1.43)	(.62)	(.69)	(.35)	(.44)
*CL*indunc*	-	.24	-	.40**	-	.35*
		(1.47)		(1.96)		(1.74)
*CM*indunc*	-	.02	-	-.01	-	.01
		(.18)		(-.10)		(.03)
*CH*indunc*	-	-.07	-	-.16	-	-.13
		(-.74)		(-1.32)		(-1.12)
*CVH*indunc*	-	.09	-	.08	-	.05
		(1.12)		(.77)		(.57)
Time dummies	*214.6***	*225.7***	*101.6***	*109.2***	*99.5***	*107.4***
Overdispersion alpha	.66**	.67**	-	-	-	-
	(.14)	(.14)				
ν_1	-	-	-	-	4.73**	4.76**
					(1.31)	(1.32)
ν_2	-	-	-	-	3.02**	2.99**
					(.94)	(.92)
Industry-specific α_i	No	No	Yes	Yes	No	No
Log likelihood	-2499.2	-2484.7	-2082.5	-2073.3	-2309.5	-2300.4
N. of obs.	2208	2208	2208	2208	2208	2208
Goodness of fit test [a]	456.7**	457.1**	1290.1**	1279.9**	836.1**	825. 8**

Note: T-statistics in parentheses (standard deviation for the overdispersion parameters). For time dummies the joint test of significance is reported.
** significant at the 5 per cent level or more; * significant at the 10 per cent level.

[a] χ^2 *test statistic of LR specification test. Model 1 is the benchmark.*

Annex Table – Data description

The model includes a total of 48 NACE 2 and 3 digits industries, grouped as follows.

No advertising and no R&D – low sunk costs: 10-11-12-13 and 14 (mining of coal, metals and stone; extraction of petroleum and natural gas); 151 and 152 (production and transformation of meat and fish); 156 (grains); 158 (fabrication of bread, tea, coffee and other alimentary products); 17 (textiles); 18 (clothing); 19 (leather); 20 (wood); 21 (paper and pulp); 22 (publishing and press); 252 and 262 (plastics and ceramics); 26 (other non-metallic products); 27 (metallurgy); 28 (metals); 292 (general machinery); 351 (ship building); 361 and 362 (furniture); 366 (other general manufacturing)

Advertising intensive – medium sunk costs: 153 and 155 (vegetables, milk and dairy products); 157 (pet food); 159 (drink and beverages); 16 (tobacco); 363 and 365 (musical instruments and toys)

R&D intensive – medium sunk costs: 241 and 242 (basic chemicals and agro-chemicals); 246 and 247 (other chemical products and synthetic fibres); 251 (rubber products); 291 (mechanical machinery); 294 and 295 (machine tools); 30 (office machines); 31 (electrical appliances, excluding domestic); 321 (electronics); 331 and 332 (medical and precision instruments); 343 (car components); 352 and 354 (railways; motorcycles)

Advertising and R&D intensive – high sunk costs: 243, 244 and 245 (paintings, pharmaceuticals and soaps and detergents); 293 (agricultural machines); 297 (domestic appliances); 322 and 323 (communication equipment); 334 and 335 (optics, photography, clocks); 341 (car production); 401 and 402 (electricity and gas); 642 (telecommunications)

Services – medium sunk costs: 45 (construction); 55 (hotels and restaurants); 65 and 66 (financial intermediation and insurance); 72 (computer and related activities); 73 (research and development); 92 (cultural and sporting activities)

Of which, the following are considered as **economies of scale** industries: 21 (paper and pulp); 22 (publishing and press); 241 and 242 (basic and agro chemicals); 245 (soaps and detergents); 246 and 247 (other chemical products and synthetic fibres); 251 (rubber products); 26 (other non-metallic products); 27 (metallurgy); 297 (domestic appliances); 31 (other electrical appliances); 321 (electronics); 322 and 323 (communication); 341 (car production); 343 (car components); 351 (ship building); 352 and 354 (railways; motorcycles).

All reported statistical data include the following *countries*: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia.

The source of macroeconomic data is the WIIW Database on Eastern Europe (www.wiiw.ac.at), 1990-2001. The variables employed are the following:

gdppc: per capita Gross Domestic Product in US$ of the countries considered

size: population in thousands of the countries considered

dist: distance in Km. from each country's capital city and an "average" European location, chosen as the city of Frankfurt

relwage: average monthly gross wage of each country with respect to the average of the countries considered

indsize: share of each industry considered in each country gross value-added