Agglomeration Premium and Trading Activity of Firms[☆]

Gábor Békés[a], Péter Harasztosi[b,*]

[a] *Institute of Economics, CERS - Hungarian Academy of Sciences*
[b] *Central European University and Magyar Nemzeti Bank*

Abstract

While most empirical studies in economic geography document a steady and positive correlation between regional density and firm productivity, the impact is not homogenous across firms. Importantly, the recent international trade literature showed that trading firms are different in terms of workforce, size or productivity. We argue that externalities that determine density premium for firms will be affected by firms' involvement in trade. Indeed, firms active in international trade may employ a different bundle of resources and be organized differently so that they would appreciate inputs and information in a different fashion and intensity. Using Hungarian manufacturing firm level data from 1992-2003 at a 150 micro-region level, we show that the elasticity of agglomeration on productivity is much larger for traders then for non-traders. As firms' trade participation is endogenous to firm performance, we offer various treatment methods of this endogeneity issue. We find that our key result is robust and well above the gap suggested by simple self-selection models.

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[*] Corresponding author: Péter Harasztosi at harasztosi@gmail.com. Central European University Department of Economics, 1051 Budapest, Nádor u. 9. Phone: +36-1-327 3020 Fax: 36-1-327 3232

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1. Introduction

The location of manufacturing firms is far from random even within a country. Firms cluster to benefit from knowledge and labor market externalities and to economize on transaction costs when working together in a supplier or innovation network. At the same time competition, advantages of proximity to resources will act against agglomeration, and hence the impact of density is a combination of many individual externalities reinforcing or offsetting each other. While most empirical studies in economic geography document positive correlation between regional density and firm productivity, the impact may not homogenous across firms. Importantly, the recent international trade literature showed that trading firms are different in terms of workforce, size or productivity and this paper will argue that this heterogeneity will influence the productivity premium of density. Furthermore, firms active in international trade may employ a different bundle of resources and be organized differently and hence, be affected differently by spillovers.

Proximity to other firms, often leads to improved performance of firms located in more agglomerated areas. Evidence of such agglomeration economies was suggested by Ciccone and Hall (1996) showing that labor productivity's elasticity with respect to density is 6 percent on average in the US. In the light of the recent emergence of evidence from several countries, it is no wonder that policymakers often try encourage agglomeration and clustering so as to boost regional productivity.[1]

Most of recent studies assumed that locations differ from each other in several areas, such as first geography features, market access or human capital. At the same time, firms are assumed to be similar. This is in odds with great deal of recent theoretical (following Melitz (2003)) and empirical evidence on firm heterogeneity. Firm heterogeneity in terms of productivity will lead to differences in trade activity as shown by Bernard et al. (2007) for the US and Mayer and Ottaviano (2008) for Europe. This evidence shows that exporters' value added is several times higher than that of non-exporters, and these firms employ more and better skilled workers, pay higher wages and are more productive than firms at domestic markets only. Hence, our focus will be on firm heterogeneity by involvement in international trade.

While these ideas of agglomeration benefits and firm heterogeneity have been developed at parallel way, research into the impact of firm heterogeneity on spatial interactions has been rather limited and mostly focused on considering general equilibrium impact of mixing firm heterogeneity and new economic geography (NEG).[2] This is why Ottaviano

[1]For more on theory see e.g. Henderson (2003), Rosenthal and Strange (2004), Duranton and Puga (2004), on evidence, Ciccone (2002), Brülhart and Mathys (2008), Combes et al. (2010), Melo et al. (2009) and for policy, see Gibbons and Overman (2011) on rural policy in the UK or Duranton et al. (2010) on cluster policies in France.

[2]Baldwin and Okubo (2006) integrated a Melitz (2003) style model into a simple NEG setting and showed that relaxing the homogenous firm assumption has implications. In Behrens et al. (2011), a traditional NEG model is extended with the introduction of efficiency differences among firms, thus

(2011) argues that such research would be useful as it could look into the intensity of agglomeration economies in the presence of heterogeneity both across firms and space. In addition to the study of differences across regions (macro-heterogeneity), the analysis of the role of differences across firms (micro-heterogeneity) is needed. This paper aims at offering evidence on the importance of this interaction by asking whether agglomeration benefit differs by firm activity in international trade.

In regards to bringing micro-heterogeneity into the analysis of agglomeration elasticity, a close paper to our approach is Graham and Maré (2010). They estimate agglomeration elasticity in New Zealand and argue that firm level heterogeneity is captured by either firm fixed effects or industry-region dummies. The paper argues that agglomeration elasticity in general has been over-estimated and the point estimate will fall to a fraction if firm heterogeneity is properly treated. The key difference with respect to this paper is that instead of controlling for the difference, we will actually emphasize it - in terms of trade status - and use heterogeneity to better understand the nature of externalities that propel better firm performance - for some firms - in denser areas.

This paper looks at how firm heterogeneity - in terms of participation in international trade - affects the measurement of agglomeration elasticity. While participation in foreign markets is closely related to productivity, we will argue that trade status itself matters. We do not model macro-heterogeneity (just control for it) but focus on how the absorption of local externalities is enhanced by the firm's trade status. In others words, we will take a reduced form equation of firm productivity and agglomeration, and investigate if the agglomeration elasticity for trading firms is greater than for non-traders. International traders might benefit more from agglomeration due to a different set of externalities enjoyed by traders or a better utilization of externalities available for all firms.

First, a set of externalities are related to the diffusion of the knowledge to trade - possibly related to administration, marketing, packaging, finding distribution or importer channels. These costs depend on the information available about the foreign market at the point of production. There is growing evidence that knowledge spillovers regarding the ways and means of commerce in an agglomerated environment tend to reduce these costs. Production has to meet international quality standards and density allows the exchange of quality improvement information as well. For example, Lovely et al. (2005) investigate the location of the headquarters of U.S. exporters. They find that firms that export to not easily accessible countries tend to be located in the proximity of each other. In a recent study, Soon and Fraser (2006) interviewing Australian exporters, find that information on overseas business opportunities and on variations in export customer preference is a valued and not that easily accessible pointer for managers. Looking at detailed customs data, Koenig et al. (2010) and Harasztosi (2011) find evidence of rather specific export

shedding light on interaction with the differences in market conditions and market size. Ottaviano (2012) models how firm heterogeneity affects the relative advantage of agglomerated areas for different firms. These endeavors indeed find a role for the interplay.

spillovers.

Second, trading firms may have a different production function where externalities are used more efficiently. Holl (2012) showed that infrastructure is important factor in explaining the effects of agglomeration. If transport infrastructure (e.g. roads, motorways, truck services) is more prevalent in agglomerated areas - due to the presence of cities - and traders use more of this, these externalities will have a more positive impact on traders than non-traders. Also, trading firms may learn more efficiently. For instance, differences in product scope may yield different reactions to agglomeration. Traders typically deal with more products - international evidence suggests that exporters produce more varieties, see, e.g. Bernard et al. (2007). Dealing with a larger amount of products presupposes advanced management and learning skills as well as higher absorption capacity. As a result, these firms are more receptive to innovations in technology and knowledge.

We will consider not only exporters but firms engaged in importing as well. This comes from findings that importers are as productive as exporters or even more productive than firms exporting only (e.g. Muûls and Pisu (2009)). Altomonte and Békés (2010) showing this for Hungarian data, argues that importers and firms doing both export and imports are engaged in a more complex production and procurement process. Exporters and importers, however might not draw the same benefits from agglomeration. Exporters require information in order to market their final product: they are in need of distribution channels, they require information on consumer behavior and on changes in regulations and standards. Importers require information for intermediate inputs: they are in need of foreign suppliers who provide input that meets their quality, price and timing requirements. Importing firms in an agglomerated environment, for example, are more easily targeted by foreign promoters and thus can import more easily from abroad.

We investigate the role of firms' international trade status in explaining heterogeneity in terms of agglomeration elasticity using firm level, location specific data from Hungary for the 1992-2003 period. In a pooled OLS model, we find a general agglomeration elasticity of 4-5 percent and for firms engaged in international trade having an additional productivity advantage of 2 percent. Moreover, looking at separate samples, while trading firms do indeed benefit from density, it is uncertain if non-trading firms gain at all. To address biases arising from firms' location selection, we use historical instruments of population density.[3]

As the trade literature (e.g. Bernard and Jensen (1999)) argues, while a part of the productivity premium of traders might be obtained after they enter foreign markets by learning, a growing body of empirical evidence suggests that bigger and better firms self-select into trader status. Indeed, it is possible that precisely the more productive firms become traders and when weighing up the different behavior of traders versus non-traders,

[3]The location of firms is endogenous, leading to omitted variable bias, see, e.g. Ciccone and Hall (1996) or Combes et al. (2010). For a comprehensive summary on methodologies and results see the meta-analysis of Melo et al. (2009).

we merely quantify the different reactions of more productive versus less productive firms in line with theories on absorptive capacity.[4]

Given that we focus on firms' trade participation, which is endogenous to firm performance, an important task of the paper is to offer some treatment of this endogeneity issue. We will apply three methods to care for this problem. First, we will increase comparability of samples of non-trading and trading firms by a matching process. Second, we offer a placebo treatment exercise to attend to the endogeneity of trading status and find that only 25 percent of the original difference is related to simple productivity differences. Finally, to absorb any time invariant heterogeneity (e.g. related to management capacity leading to superior performance) at the firm level we use firm fixed effects.

Furthermore, to test robustness of results from other angles, we add spatial lags, extend results for the number of firms instead of density, and consider the impact of large or multi-site firms. All these methods confirm our results.

The rest of the paper is organized as follows. Section 2 describes the empirical strategy and our estimation methods. Section 3 introduces the dataset and discusses data related issues. In Section 4, we present the results estimated in various models followed by some robustness checks and a comparison of exporters and importers. The last section concludes. In the Appendix we present additional descriptive statistics and robustness checks.

2. Model and estimation

This paper looks at how international trading activities of firms affect the agglomeration elasticity of productivity. In this section we formally present the inclusion of trade status into the production function and discuss challenges of directly estimating a reduced form equation. Various steps estimating the impact of agglomeration and trade on productivity are presented as well.

We assume that the production function takes a standard Cobb-Douglas form:

$$Y_{it} = A_{it} L_{it}^{\beta_L} K_{it}^{\beta_K} \tag{1}$$

[4]Theoretically the relationship between self-selection, TFP and agglomeration is not straightforward. In a model where local features do not affect productivity, nationally more productive firms would become traders, and in our model, we would just wrongly assume a trader premium for what is effectively a productivity premium. However, let us assume that the productivity distribution of firms depends on local characteristics (agglomeration) as suggested by the literature following Ciccone and Hall (1996), but the cut-off point for self-selection is determined at the national market. In a less agglomerated area, one should find more unproductive firms and hence, the difference between non-trader and trader TFP would be actually higher in less agglomerated regions. Thus, at a simple cross-section OLS, one should see agglomeration negatively correlated with the difference between traders and non-traders.

where Y stands for the real value-added of firm i at time t, while L and K are the labor-force and the real capital stock used by the firm. Following Henderson (2003) we assume that agglomeration economies influence the total factor productivity of firms, A_{it} in the following fashion:

$$A_{it} = D_{rt}^{\gamma+\eta X_{it}} U_{it} \tag{2}$$

Where D_{rt} denotes the agglomeration variable in region r where firm i is located in time t. X represents the firms' trading status and U_{it} captures unobservables. After taking logs on both sides of eq. (1) and (2) the production function may be written as:

$$y_{it} = a_{it} + \beta_L l_{it} + \beta_K k_{it} \tag{3}$$

with log productivity defined as:

$$a_{it} = (\gamma + \eta X_{it}) d_{rt} + u_{it} \tag{4}$$

with lower case letters denoting the corresponding logarithmic values.

2.1. Tackling estimation issues

The key coefficients of our interest are γ and η. If u_{it} is exogenous, then by substituting (4) in (3) coefficients can be estimated by OLS. The γ coefficient represents general agglomeration elasticity and is expected to be positive. Coefficient η expresses the additional elasticity for trading firms. If it is positive and significant, then trading firm in one percent denser locations are $(\gamma + \eta)/100$ percent more productive

However, exogeneity does not necessarily hold. To discuss these issues let us assume that u_{it} takes the form of

$$u_{it} = \omega \mathbf{ctrls}_{it} + \mu_r + \psi_{rt} + \phi_i + \epsilon_{it} \tag{5}$$

where $\mathbf{ctrls}_{it}$ represents time-variant firm characteristics, μ_r represents time invariant local characteristics, ψ_{rt} local productivity shocks, ϕ_i time invariant unobservable characteristics at the firm level and residual ϵ_{it}.[5] There are several estimation issues here, to be briefly discussed below.

Firstly, we add additional controls such as trading status and foreign ownership. Both may affect TFP independent of agglomeration. Note that ownership status is introduced to capture changes in the management and possible changes in the quality and the composition of the workforce.[6] Consequently, we estimate (4) and 3) together, which, after taking logs and adding $\mathbf{ctrls}_{it}$ for firm level controls.

[5] Residual ϵ_{it} is equivalent of a exogenous error term in all upcoming models.

[6] On privatization and the impact of foreign takeover, see Brown et al. (2006)

Second, input variables (k_{it}, l_{it}) in the production function can be correlated with u_{it}; in the case of labor, we can either have $Cov(l_{it}, \phi_i) \neq 0$ or $Cov(l_{it}, \epsilon_{it}) \neq 0$. In practice this means that time invariant firm specific unobservable characteristics, such as organization structure or management skills may affect both the input choice and the value added of the firm. Furthermore, one-off shocks that are observable to the manager but not to the econometrician may cause a simultaneity problem: if the manager foresees or anticipates a positive shock, she may hire more workers or invest more into machinery as a response.

To tackle endogeneity of inputs, we adopt the approach offered by Olley and Pakes (1996) (OP)[7] and estimate equation (4) having estimated (3) first. We prefer this specification to the joint estimation, given that the modified OP allows for comparing firms across various trading status. The log of firm-level total factor productivity is calculated using 2-digit NACE sector estimates of the production function. This calculated value we denote with tfp_{it}.[8] Hence, we estimate eq. (6):

$$tfp_{it} = (\gamma + \eta X_{it})d_{rt} + \omega \mathbf{ctrls}_{it} + \mu_r + \epsilon_{it} \tag{6}$$

The OP method is adaptable when firms based on unobserved productivity shocks simultaneously decide to exit or to continue production and decide on the quantity of production inputs they require. We modify the standard OP procedure to reflect to the fact that trading firms face different input prices. Exchange rate changes over the examined period might induce a measurement error in the prices used in the estimation. To account for the trading status in the production function we used a modification of the OP procedure as proposed by Amiti and Konings (2007) and Altomonte and Békés (2010). This carried out by introducing exchange rates as domestic and imported materials are distinguished in value added as well as changing the OP procedure's investment control equation to control for trade status and the origin of the input; the procedure is described in detail in the Webappendix.

Third, a problem arises from using aggregate indicators as regressors on firm-level data. As pointed out by Moulton (1990), regressing aggregate variables on micro-level observations has the pitfall of underestimating the standard errors of the coefficient estimate. This implies that the null-hypothesis of no effect of the group level variable is rejected with a higher probability. In our regressions, agglomeration variables are aggregate variables and one might run the risk of underestimating the variance of the coefficient related to them. To control for the bias in the standard errors, we follow Moulton (1990)

[7]The other option for handling the endogeneity of the inputs and agglomeration variables together would be to use dynamic panel data models (see Bond (2002)). Our finding is, however, that GMM estimations on the Hungarian data show rather unstable results with the starting point being excessively important.

[8]We denote estimated/claculated TFP differently from the theoretical one, a_{it}. Note, that a can only be estimated together with the residual of the production function.

and cluster standard errors according to the spatial unit of aggregation. Our baseline results will thus use one-step and two-step OLS with Moulton correction of standard errors.

Fourth, note that agglomeration variable, d_{rt} may be endogenous to the production function with $Cov(d_{rt}, \mu_r) \neq 0$ and $Cov(d_{rt}, \phi_i) \neq 0$. A correlation may arise due to unmeasured location specific characteristics, such as natural resources that attract firms and workers as well as increases the productivity of local firms. Additionally, there are unobserved firm characteristics that can make location endogenous. For instance, Combes et al. (2008, 2010) highlight the importance of the spatial sorting of better workers to cities. The abilities and skill of workers, quality of management will be reflected in the performance of the firms.

Time invariant unobservables, transitory local shocks, denoted by ψ_{rt}, may cause an additional problem: $Cov(d_{rt}, \psi_{rt}) \neq 0$. Furthermore, local transitory shocks can affect agglomeration and a firm's value added simultaneously, as firms may observe local shocks and simultaneously hire or lay off workers. For instance if demand dropped for goods produced dominantly in one region, several local firms may close down (hence changing sectoral concentration) and workers may move to other locations (affect local agglomeration).

To address the endogeneity problem due to a correlation between density and productivity (caused by location specific characteristics affecting both variables), we rely on an instrumental variable approach. That is, we instrument agglomeration (d) with historical values of population density. As argued by Ciccone and Hall (1996) or Combes et al. (2010), this is a valid instrument it is correlated with agglomeration, and should not affect present day firm TFP. Past population density captures location amenities, such as good climate, easy transport or nutrition access that affects spatial distribution of people but does not affect present productivity. For Hungary the Central Statistical Office compiled population data from previous census data consistent with current geographical units dating back to 1880.

Importantly for our exercise, the introducing instrumental variable technique makes estimating the trade status $\times$ agglomeration cross term problematic. Proper estimation would require separate instrument for density and for the density trader cross term, which we do not have. Instead, we opt for measuring agglomeration elasticity separately for traders and non-traders.

We set up three sub-samples, one for firms that never trade, one for firms that trade occasionally (i.e. includes firms that start and then stop trading, or trade temporarily), and one for firms that always trade.[9] This specification allows us to compare the agglomeration elasticity coefficient across sub-samples:

[9] In this latter sample firms are allowed time to build, that is, firms not trading in their first year in the sample are still considered always traders. This first year is, however, omitted from the analysis.

$$tfp_{it}|\mathbf{trading} = \gamma d_{rt} + \boldsymbol{\beta} ctrls_{it} + \epsilon_{it} \tag{7}$$
$$\mathbf{trading} = (never, occasionally, always)$$

In the model described in eq. 7 we instrument d_{rt}.

2.2. Methods to manage trade status endogeneity

In addition to the aforementioned estimation issues, the potential endogenity of trading firms yields additional problems. Trading status can be endogenous as suggested by correlations and selection shown by Bernard and Jensen (1999, 2004) Internationalized firms are bigger in size, pay higher wages and are more capital intensive. Importantly, as trading firms need to pay a fixed cost when entering foreign markets, only the most productive can overcome this sunk cost and these firms will self-select into the trading status (Melitz, 2003). This implies that $Cov(X_{it}, \phi_i) \neq 0$.

We propose three separate procedures: adding firm fixed effects to treat unobserved characteristics leading to self-selection into trade, increasing the comparability of sample by cutting outliers (hence, avoiding the bias caused for instance by large trading firms) and carry out a pseudo treatment exercise modeling self-selection explicitly.[10]

Our first approach to tackle the endogeneity caused by time invariant unobservable characteristics is to move to firm fixed effect panel model. In addition to firm level unobserved heterogeneity problems, firm fixed effects estimation is also able to attend to issues regarding (time-invariant) regional unobserved heterogeneity, initial conditions. That is, fixed effects model can also capture amenities that created past productivity and agglomeration. Hence we do not use instruments in this model:

$$tfp_{it}|\mathbf{trading} = \gamma d_{rt} + \boldsymbol{\beta} ctrls_{it} + \phi_i + \epsilon_{it} \tag{8}$$
$$\mathbf{trading} = (never, occasionally, always)$$

Second, given that traders are different - they are larger, more capital-intensive and more likely to be foreign-owned - one might argue that running regressions with the purpose of comparing these two subsets of firms runs the risk of making comparisons across different parameter distributions. Hence, the result of a different agglomeration

[10] In terms of an empirical investigation strategy, one could add TFP_{t-1} to the right hand side, thereby controlling for an a priori (self-selection) difference. This gives a significant coefficient and a somewhat reduced but still large difference between traders and non-traders. At the same time, it raises several econometric issues, e.g. serial correlation, as argued by Arellano and Bond (1991). Unfortunately, past experience regarding our data suggests that the GMM approach would, however, give arbitrary results based on a number of moment conditions used.

coefficient of traders and non-traders is affected by the fact that we do not restrict other parameters to be equal across firms.

To attend to this we rely on matching of the samples. The procedure, taken from Imbens and Wooldridge (2009) consists of two steps: first, a logit regression is run to express the conditional probability of being a trader. Equation controls are productivity, ownership, size, agglomeration and also time, region and sector fixed effects. In the second step, having obtained the propensity score for each observation, the subs-ample of traders is trimmed by excluding the highest 25 percent of the score distribution of traders. For non-traders the lowest 25 percent of the respective score distribution was dropped. Consequently, the sample size is reduced. When employing the matching technique we use model described by 7.

Third, we suggest a placebo treatment exercise with pseudo-trader status. This tests what part of the heterogeneous results across subsamples is through heterogeneous impact form the TFP dimension, and what part is through the trading status instead.

The basic idea behind the exercise is fairly simple. Part of the difference we place on trade status is due to productivity owing to the self-selection process of most productive firms into trade - at a national level. We aim at grasping the size of the bias rather than treating it explicitly. We do this, by first predicting the trader status and then using this predicted (rather than actual) trader status in our main regression. If we find the predicted trade-agglomeration elasticity across likely-to-be-trader firms to be close to the one observed in the real data, then it is likely that most of our findings are actually due to such a selection bias. Otherwise, if we find that the placebo coefficients across groups defined by pseudo-trade are similar, selection to trade is not at work.

We start by assigning a pseudo trading status to firms implied by a simple probit estimation, where P, the probability of being a trader, is determined by its TFP_t. The firm is a pseudo-trader if $P > \zeta$, where ζ is a uniform random variable on the zero-one interval, so that the expected share of (pseudo-)traders match the mean share of traders in the data. This provides us with one possible realization based on firms' first year of estimated productivity in the sample. Instead of defining firms by their actual trading status, we use the predicted indicator, and accordingly group firms as never and always traders. (Note that once again we skip firms switching trade status.) Using these sub-samples, based on pseudo-trader status, we re-estimate our models. To obtain distributions for the agglomeration coefficients, we generate ζ and run the regressions 500 times. This allows us to calculate means and standard errors from the empirical distribution given by the replications. Having done this exercise, we can compare the placebo results to those obtained on sub-samples defined on real trade status.

3. Data, variables and descriptive statistics

The empirical analysis uses the CeFiG database, a panel of Hungarian manufacturing firms between 1992-2003 with very detailed firm-level information on balance sheets and trading activity and location. The panel contains on average 15000 firms per year of the manufacturing sectors[11].

Firm performance and activity

The balance sheet information in the data provides the necessary variables to estimate firm performance by total factor productivity (TFP) at the 2 digit NACE sector level. We defined foreign ownership if at least 5 percent of subscribed capital is held by foreigners. The labor variable is the average annual employment reported by the firms. We included firms with at least five employees reliability of the reported figures. At this sample, firms on average employ 62 workers.

The capital variable is constructed as follows. The nominal capital is calculated as the sum of fixed assets. To construct real capital and handle the problem of different vintages we use the perpetual inventory method. In the transition to market economy firm re-evaluated their capital stock which allows us to accumulate real investments since 1992. Deflator to produce real values of materials, output, value-added and investments are provided by the Hungarian Statistical Office's National Accounts at the two digit sectoral level.

The balance sheet data have been merged with customs information, and thus, we can see whether a firm is engaged in exporting or importing activity in the given year. In this study, we will refer to a firm being a trader ($X_{it} = 1$) in a given year if it is either exporting or importing (or both).

Table 1: Exporting and importing premia across manufacturers

	exporter premia	importer premia
log of employment	1.525	1.313
log of value added per worker	0.388	0.533
log of TFP	0.850	0.947
log of average wage	0.395	0.456
log of capital per worker	0.346	0.357

Each row shows coefficient estimates variables in the first column regressed on exporter and importer dummies. As independent variables are in logs the coefficient 1.52 with the log of employment implies: exp(1.52)-1 = 350% higher employment on average in exporter firms.

In our sample, 40 percent of firms does not trade at all, 15 percent imports but does not export, 7 percent exports without directly importing and 38 percent does both export and import. Trading firms differ from non-traders in a number of characteristics.

Table 1 illustrates the difference across trading firms in Hungarian manufacturing. It shows coefficient estimates of exporter and importer dummies regressed on the variables in the first column. In line with international evidence, we see that traders are more

[11]For a detailed description of the dataset see Békés et al. (2011).

productive, more capital intensive and more than three times larger than non-traders. We collected additional descriptive statistics on the number of observations and main variables in Tables 10 and 11 in the Appendix.

Location issues and the agglomeration variable

The Hungarian company data at our disposal point to the locations of the headquarters of firms, defined at the micro-region level. Micro-regions are the smallest administrative EU units bigger than a settlement. In Table 2 Hungarian spatial units are summarized in harmony with the EU zoning. Going from larger to smaller, the administrative units are as follows: county (*megye*), micro-region (*kistérség*) and municipalities. Hungary consists of 20 counties, with the stratification considering the capital, Budapest as a separate entity; this corresponds to the NUTS 3 level EU regional policy unit. There are 150 micro-regions, and a county comprises eight micro-regions on average. Each micro-region contains approximately 4-10 towns and villages, their average size is 620 km^2 with 70 thousand inhabitants. See the Tables in the Webappendix for the summary statistics of the micro-regions.[12]

Table 2: *Summary of Hungarian administrative spatial zoning*

EU level units	Hungarian equivalent	number	avg. size km^2
NUTS2	EU administrative region	7	13861
NUTS3	20 regions (megye)	20	4651
NUTS4	micro regions (kistérség)	150	620
NUTS5	municipalities	3125	30

We define agglomeration (d_{rt}) variable as the logarithm of the employment of all manufacturing firms in the same micro-region. Obviously, agglomeration does not only have positive effects. As duly shown in Ciccone and Hall (1996), the empirically measured net agglomeration effect is a sum of (positive) externalities and (negative) congestion effects. The agglomeration variable is the same for all the firms in the given region within a year as it contains the firm itself and we control for firm employment in a separate variable.[13] The variable expresses the size of the active local manufacturing labor market. We introduce an additional measure of dense economy in Section 6.2.

Identifying firms by a single micro-region address may cause problems and biases in the case of multi-plant firms. First, we bias agglomeration measures towards more urban areas, where firms have their administrative center (also causing a downward bias for

[12]We kept only firms in the sample that do not change location over the period: only 3 percent of the firms have two or more location.

[13]Our results are robust in the alternative specification when excluding own employment.

regions that may host manufacturing facilities only). Second, TFP of multi-plant firms should be a combination of productivity measured at the plant level and should be affected by several agglomeration externalities, not just one. Note that one would make no error when a multi-plant firm has an administrative office in the city, but a production facility in a satellite settlement within the micro-region. Unfortunately, given the data limitations, we cannot measure plant productivity and relate it to plant-level agglomeration measures. However, to check for this, we use a different dataset and find that over 90 percent of firms have one site only; furthermore, for the remaining 10 percent the main site covers two-thirds of the employees, which suggests that the bias does not really give cause for concern (for details, see Appendix). The multi-plant problem necessitates the focus on manufacturing: in the service sector about third of the firms are multi-site with four or more locations.

Instrument

To instrument manufacturing population density we use population census data from 1880. The statistic is provided by the Hungarian Statistical Office. They have compiled information from the all past decennial census with the settlement structure updated to be consistent with the post 1990 Hungarian municipality structure. We have aggregated the population data to match the geography of the firm level database. In Table 3 we present the partial correlation coefficient between our agglomeration measure and log 1880 population density, the instrument candidate as well as t-ratios for the 1880 population density from OLS regressions of agglomeration on the instruments and controls. We provide statistics both for a single yea and for the whole panel. The statistics confirm the relevance of the instruments.[14]

Table 3: Partial correlation of instrument and agglomeration variable

	partial correlation	t-ratio	
		1997	all years
ln Pop dens 1880	0.909	55.17***	173.23***

[14]We have also tried other years as well, from 1890 to 1910, they yield very similar results. Additionally we have calculated soil characteristics from the European Soil Database (EUSOILS) as Combes et al. (2010). In the case of Hungary the variance in the soil characteristics cannot sufficiently explain distribution of population. We also found that inclusion of more than one instrument or trying to augment past density with geology variables result in overidentification.

4. Results

4.1. Basic results

The baseline results, from OLS estimations of equation 6, are presented in Table 4. The first half of the table (cols 1-3) reports results from one-step estimations of the augmented production function, while the second half (cols 4-6) covers the two-step estimations with TFP estimated first. In all regressions, standard errors are clustered at a micro-region level, as suggested by Moulton (1990).

Column (1) shows the cross section result on a (mid-sample) single year, 1997, while in column (2) we include additional regressors: the agglomeration-trader cross-term as well as a set of dummy variables for firms' trade status, foreign ownership, sector and region. Column (3) shows pooled OLS with year dummies. All estimated coefficients are significant with the expected sign.[15]

The agglomeration coefficient is positive and significant. It suggest, via the log-log specification, that firms in one percent more dense regions are 0.04-0.045 percent more productive. In column (2), we add the agglomeration-trade status cross terms, which is also positive and significant as expected. The productivity of traders is higher by 0.021 percent in one percent more dense areas, with the plain agglomeration elasticity declining to 0.036 percent. For the whole period, we get similar results, with a lower value for the cross term. In the fourth to sixth column of Table 4 we show results from the two step estimation, where TFP is first estimated by the modified OP procedure. Results are in line with previous findings.[16] Overall, we find these figures on agglomeration are in line with international evidence of 3-6 percent (Melo et al., 2009).

To control for endogeneity of the agglomeration variable we use instrumental variable strategy. We take equation (7) and instrument agglomeration (d_{it}) with past population density (Z_i). As noted in the methodology section, we lack a separate instrument for the cross term and as a solution we estimate on separated subsamples for trading and non trading firms. The main results are summarized in Table 5. The table contains six columns. The first three are OLS estimations on subsamples of firms that never, occasionally or always trade. The OLS estimates for agglomeration elasticity range from 7 to 12 percents as trading activity increases across samples. That is we find significantly higher agglomeration elasticity for traders. The next three columns are the instrumented counterparts with diagnostic statistics for the IV are indicated at the lower panel of the

[15]Coefficient on the production factors are significant and of the expected sign. Hungarian production is rather labor intensive, the elasticity of value added with respect to labor is around 75 percent. The same figure for capital is about 20 percent. Previous studies using production functions for the Hungarian manufacturing sectors find similar results, see e.g. Kátay and Wolf (2008). Adding industry level cross terms with K, L make no difference either - results available on request.

[16]We have also tried different TFP estimates in the case of the last three columns: Levinsohn and Petrin (2000) technique, FE estimates. Results, in line with Table 4, are available upon request.

Table 4: OLS regression results

dep: var	Value added			TFP		
sample:	1997	1997	all years	1997	1997	all years
labor	0.782***	0.757***	0.746***			
	[0.0219]	[0.0218]	[0.0201]			
capital	0.236***	0.203***	0.211***			
	[0.00679]	[0.00467]	[0.00317]			
agglomeration	0.0452***	0.0361***	0.0435***	0.0416***	0.0363***	0.0516***
	[0.0104]	[0.0106]	[0.00706]	[0.0121]	[0.0113]	[0.00796]
agglo. X trader		0.0217***	0.0109***		0.0227***	0.0133***
		[0.00711]	[0.00411]		[0.00595]	[0.00354]
trader		0.137*	0.201***		0.417***	0.429***
		[0.0717]	[0.0392]		[0.0682]	[0.0415]
foreign own.		0.140***	0.111***		0.284***	0.318***
		[0.0276]	[0.0289]		[0.0214]	[0.0235]
dummy: time			yes			yes
dummy: sector	yes	yes	yes	yes	yes	yes
dummy: region	yes	yes	yes	yes	yes	yes
Observations	8870	8870	96709	9651	9651	105683
R-squared	0.754	0.765	0.764	0.136	0.262	0.270

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moulton corr. standard errors in parentheses

The Table shows two blocks of firm level regressions on agglomeration with different dependent variables: real value added on the left, firm level TFP. Each block contains 3 equations: two single year equation without and with agglomeration and trader cross terms and firm level controls and one regression on the pooled sample.

Table.[17] Compared to the OLS estimates the results are smaller in all subsamples. We do not find significant agglomeration elasticity for non traders and results suggest that for traders the coefficient is about ten percent.

We carry out several robustness tests. We address spatial correlation, and consider the stability of results.

First, regions are not randomly placed and hence, we need to consider their spatial structure. When choosing micro-region level stratification as the basic unit of boundaries to external economies, we neglect the possibility that the agglomeration ranges further than this artificial unit. Artificial division of space causes a problem if it separates regions that are otherwise bound together economically, e.g. share a labor market or two regions

[17]F-statistics from regressions on all exogenous variables show that instruments provide a good fit. Additionally, Cragg-Donald statistics are in all cases above the critical value reported in Stock and Yogo (2002). To address possible bias arising from weak instruments we also report Stock-Wright S statistic (Stock and Wright, 2000) which test the null hypothesis that coefficients of the endogenous variables are jointly zero. The test statistics imply that the null hypothesis can be rejected only in the case of trading sample. This implies that in the case of never traders the agglomeration coefficient is in fact zero.

Table 5: OLS and 2SLS regression results by trading activity - separate samples

Dep. var.: VA	never	occasionally	always	never	occasionally	always
agglomeration	0.0694***	0.0994***	0.125**	0.0192	0.0734**	0.106***
	[0.0055]	[0.0052]	[0.0063]	[0.0206]	[0.0296]	[0.0344]
foreign own.	-0.0314***	0.316***	0.460***	-0.0164	0.358***	0.411***
	[0.02865]	[0.0312]	[0.0321]	[0.0234]	[0.0285]	[0.0303]
instrument:						
ln Pop dens 1880	no	no	no	yes	yes	yes
dummy: sector	yes	yes	yes	yes	yes	yes
dummy: region	yes	yes	yes	yes	yes	yes
dummy: year	yes	yes	yes	yes	yes	yes
First stage: F-stat				44.65	42.98	38.62
First stage: R-sq.				0.8537	0.8698	0.8669
Cragg-Donald Stat.				7417.55	16252.09	6389.3
Kleibergen-Paap stat.				44.65	42.98	38.62
Stock-Wright LM S stat.				0.78	5.38**	9.67***
F-stat.				143.51	245.79	103.49
Observations	17330	43848	22054	25588	56686	23409
R-squared	0.046	0.108	0.128	0.145	0.195	0.246

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Moulton corr. standard errors in parentheses

Each column show the results from regression eq.7 on three separate samples of firms: never traders, sometimes or occasionally traders and always traders. We instrument agglomeration with log of 1880 density in columns 4 to 6.

share the same natural resource: a mountain with ores or a river. This may lead to a spatially correlated population size in the neighboring regions and agglomeration elasticity actually rises for traders.

To control for agglomeration effects not bound within micro-regions (i.e. spatial autocorrelation), firm-level regressions including characteristics of the immediate neighboring micro-regions are estimated.[18] Note that controlling for this effect is different from the fixed effects specification as it allows for time variance in the characteristics of the wider neighborhood of the micro-region.

The neglect of spatial dependence induces problems. For example, a prospering and growing neighborhood might attract employment and generate productivity spillovers at the same time. Therefore, own density and productivity will be correlated positively to both productivity and the density of neighbors. If this effect is time variant, micro-region fixed effects will not capture it. Ignoring such spatial autocorrelation will result in the overestimation of the agglomeration effect. The results from fixed-effects regressions including spatial lag variables for neighboring manufacturing density and productivity are

[18] For further details, see the Appendix.

displayed in Table 14 (Appendix) - with no change in our basic inference about traders' agglomeration elasticity. At the same time,

Finally, let us make some observations on the stability of these results. As the premium in this strategy is identified through time-variation in density, the results may not actually capture if trading firms are more productive in denser areas, and we might be looking at simultaneous changes in TFP and very small changes in density (see potential pitfalls noted by Holmes (2010)). To make sure this is not the case, we look at the variation between two periods of time to see if variation in density measures is sufficient. In Table 16 (Appendix) we present a transition matrix by deciles. Most deciles show substantial variation over time, i.e., identification is not solely the result of very small changes in density.[19]

Overall, trading firms show about 10-11 percent agglomeration elasticity, while non-traders may gain 0 to 1. The result implies that when agglomeration is measured with the density of the workforce, trading firms show a higher productivity in a more agglomerated environment while across nontrading firms the agglomeration elasticity is small or insignificant. To evaluate the difference between the agglomeration elasticities, we carry out a simple F-test on the difference between coefficients of non-traders and always traders. The difference is significant at a 5 percent level which remains when controlling for spatial lags.

4.2. Endogeneity of trading status

In this section we provide three approaches to tackle the endogeneity of trader status. First we employ firm fixed effects estimation. Second, we use a simple matching technique to improve the overlap in covariate distributions. Lastly, we develop a placebo treatment exercise.

The first possibility to tackle the bias caused by time invariant unobservable characteristics is to use fixed-effect (FE) estimation strategy with the sample of firms is divided into groups. Results displayed in Table 6 indicate the strong difference of elasticities estimated for traders versus non-traders. The evidence implies that firms that are involved in international trade show much higher productivity in agglomerated economies than non-trading firms. Also, one can observe a ranking of agglomeration elasticity as trade involvement over the sub-sample increases, both in terms of significance and magnitude.

Non-trading firms on average do not show significantly higher productivity in a more agglomerated environment, while always traders exhibit a 19.1 percent elasticity. Occasional traders show an elasticity in between non-traders and always traders. Results showing that always and occasionally trading firms show higher than 0.1 percent productivity in a one percent more dense economic environment suggest that a considerable part of the general agglomeration elasticity is due to international traders.[20]

[19] Further evidence on time variation is available on request.

[20] Agglomeration benefits may enter (Glaeser et al., 1992) via localization (own industry effects) and

Table 6: Agglomeration premium by trading activity - separate samples FE

Dep. Var.: TFP	firms that trade in their time present		
	never	occasionally	always
agglomeration	0.0434	0.101*	0.191***
	[0.0365]	[0.0520]	[0.0605]
foreign ownership	-0.0182	0.00741	0.0657***
	[0.0207]	[0.0247]	[0.0156]
dummy: year	yes	yes	yes
constant	yes	yes	yes
Observations	17330	43848	22054
R-squared	0.089	0.096	0.194
Number of id	4530	7659	3608

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Moulton corr. standard errors in parentheses

Each column show the results from regression eq.8 on three separate samples of firms: never traders, sometimes or occasionally traders and always traders.

Foreign ownership in fixed effect specifications refers to change, mostly foreign takeover during our period of observation. As this is a period of rising foreign activity, this may be an important control in addition to firm fixed effects. Results show that this has a positive and significant effect on TFP for trading firms only.[21]

Note that the coefficient estimates by the FE model are considerably higher than estimates by OLS. While agglomeration in former central-planning countries tend to be higher than elsewhere[22], this is not the key explanation, as OLS results are close to international estimates. The key culprit is different behavior of spatial sorting. We find that in our sample the agglomeration coefficient changes with introducing more precise controls for heterogeneity, especially for location. Adding geographical controls with increasing precision and finally firm fixed effects increases agglomeration coefficient.[23] That is, the high agglomeration coefficient is not entirely due to the fixed effects technique. The more precisely we control for the average productivity of the location the higher the elasticity gets. It seems spatial sorting is complex in Hungary, and is not fully explained by the selection mechanism emphasized by Syverson (2004), Combes et al. (2012)[24]

urbanization (general diversity). To identify the source of the traders premium we included agglomeration variables separated by industry. We find that localization (own industry concentration) is significant in both the never- and always trader sub-samples, urbanization (other industry concentration) is significant for the traders only. Thus, the traders premium is more connected to cities than isolated trade platforms. Results may be found in the working paper version.

[21] All results presented in this paper are available in FE specification on request.

[22] See Brülhart and Traeger (2003) or Foster and Stehrer (2008)

[23] Calculations are available upon request

[24] It is possible that location choice of firms in transition economies in terms of cities and villages

Second, we consider a mechanism to control for different sample characteristics of non-trading and trading firms. As traders are different, running regressions with the purpose of comparing these two subsets of firms runs the risk of making comparisons across different parameter distributions. Hence, the result of a different agglomeration coefficient of traders and non-traders is affected by the fact that we do not restrict other parameters to be equal across firms. As indeed is evident from Table 6, foreign ownership might have a different effect on trading and non-trading firms. To see whether this issue biases our inference, we rerun our regression on more comparable samples as well. Here, we rely on the propensity score matching approach to improve the overlap in covariate distributions. The results, displayed in Table 7 in the Appendix, show that a higher agglomeration premium for traders is still present when using samples where traders and non-traders are matched to be more similar. At the same time, we can observe that the agglomeration elasticity of never traders is now higher, though still not significant. It increased from 2 to almost percent 4 percent. Results suggest when we control for trade self selection on observable characteristics, we find that part of our result for the higher agglomeration elasticity for traders is due to endogeneity of trade status. But it explains only a small fraction of our findings.

Table 7: Agglomeration coefficient estimates actual and matched samples

	data		matched samples	
	never	always	never	always
agglomeration	0.0192	0.106***	0.0382	0.102***
	[0.0206]	[0.034]	[0.0237]	[0.0324]

Each column show the results from regression eq.7 on three separate samples of firms: never traders and always traders. We instrument agglomeration with log of 1880 density. Samples are trimmed as suggested by Imbens and Wooldridge (2009) for the probability of being trader

Our third method is based on running a placebo treatment regression and predicting a pseudo-trader status. As proposed in section 2, if we find the predicted trade-agglomeration elasticity across likely-to-be-trader firms close to the one observed in the real data, we can assume that most of our findings are actually due to such a selection bias. In the opposite case, i.e., if we find that estimated elasticities for pseudo-traders and non-traders are similar, we can infer that results obtained from the actual data are not entirely due to selection.

In Table 8 we compare our placebo results to those obtained from the actual data. The first two columns replicate the first row of Table 8 for those firms who never and for those who always trade. The last two columns show the average of the corresponding

is related to transition specific issues, as the economy breaks away from central planning. While an interesting topic, this is outside the scope of this paper results over the 500-500 replications on the placebos. Standard errors are presented in brackets.[25]

Table 8: Agglomeration coefficient estimates actual and placebo

	data		placebo	
	never	always	never	always
agglomeration	0.0192	0.106	0.0457	0.0621
	[0.0206]	[0.034]	[0.003]	[0.007]

The first and second column use the sample of never trading firms and always trading firms respectively. In the third and fourth columns results are collected from the placebo treatment exercise. Here, the never and always trader samples are created from the generated trading status, coefficients and standard errors are obtained from the 500 replications.

The results show that while the agglomeration effect differs greatly between actual traders and non-traders (0 to 10 percent) it is very similar between pseudo-traders and pseudo-nontraders (4.5 to 6 percent). F-test cannot reject the null that coefficients of pseudo-traders and pseudo non-traders are the same, while a similar null hypothesis is rejected at 5 percent for the actual data. This finding suggests that even controlling for initial productivity, trading behavior itself remains an important determinant of agglomeration elasticity. [26]

4.3. Exporters and importers

Finally, traders' agglomeration elasticity is further investigated by refining trade measures. The trading status is examined separately for exporters and importers taking the direction of trade into account.

Following the voluminous literature on how exporters differ from other firms in many respects, recent studies have suggested that import activity is an equally important predictor of firm heterogeneity (see, e.g., Altomonte and Békés (2010)). No doubt, spillovers of information about the foreign market and foreign business channels are of key importance both for exporters and importers. However, exporters and importers might not draw the same benefits from agglomeration. Furthermore, it is important that the set of export and import partner countries differ in Hungary. While Germany and other European countries are the foremost partners in both cases, the share of imports from

[25]Details and robustness tests are available on request.

[26]A different approach would be to test if the agglomeration effect is strictly increasing with productivity, i.e. more productive firms benefit more from agglomeration. A quantile regression (comparing means of subsamples conditional on the independent variable, in this case: productivity) shows that traders along the full spectrum of productivity enjoy significant additional agglomeration benefits. Details available on request.

Table 9: *Regressions for exporters and importers separately*

Dep. Var.: VA	never	always	never	always
agglomeration	0.0155	0.143***	0.0141	0.115***
	[0.0224]	[0.0329]	[0.0164]	[0.0356]
foreign ow.	0.0609**	0.395***	-0.0557***	0.374***
	[0.0299]	[0.0411]	[0.0192]	[0.0432]
instrument:				
ln Pop dens 1880	yes	yes	yes	yes
dummy: sector	yes	yes	yes	yes
dummy: region	yes	yes	yes	yes
dummy: year	yes	yes	yes	yes
First stage: F-stat	46.67	31.15	50.85	34.23
First stage: R-sq.	0.8756	0.8283	0.8556	0.8702
Cragg-Donald Stat.	11449.83	6018.96	9664.3	8022.25
Kleibergen-Paap stat.	46.67	31.15	50.85	34.23
Stock-Wright LM S stat.	0.45	16.52***	0.68	10.04***
F-stat.	168.83	76.56	149.77	
Observations	37108	26605	29018	34057
R-squared	0.155	0.223	0.148	0.218

Moulton corrected s. errors in brackets
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Each column shows results from separate regression. The first two are 2SLS regressions and use the full sample of firms with the modification that trader is now exporter or importer. The last two columns estimate eq. 7 on two different samples, always exporters and always importing firms.

Asian and Far Eastern countries increased substantially over our sample period. Given the cross-cultural differences and language barriers involved, the access to trade related information might be more limited in the case of imports.

To assess the relative importance of the type of trade for the agglomeration elasticity, regressions are estimated both on the separated sample and on the full sample with cross terms of trade status and agglomeration included. The results are displayed in Table 9, where the first two columns present the full sample regressions for examining exporters' and importers' elasticity. Their specification is analogous to the last column of Table 4. The last two columns show within estimations for specific subsamples of firms, always exporters and always importers. The regressions are analogous to the third column of Table 6. Results imply that both exporters and importers show higher productivity in a more agglomerated environment than non-traders. Note however that always exporters and always importer subsamples overlap due to the large number of two-way traders in the Hungarian economy. As Altomonte and Békés (2010) suggest importers and two-way traders carry out a more complex production and procurement process which requires higher skills in labor and management. Agglomeration might be a better environment in order to satisfy their special needs.

5. Concluding Remarks

This paper investigated whether agglomeration has a larger effect on the productivity of firms engaged international traders than on those that only source and sell domestically. We used region specific firm level data from Hungary containing information on export and import status of firms. Our results indicate that the intensity of agglomeration economies depends on the trade status of firms, both exporters and importers gain more from agglomeration than non-traders. This result is qualitatively robust when controlling for the difference in the characteristics of trading and non-trading firms, as well as when including a spatial lag structure or combining employment density with the number of firms.

Our result suggests that apart from traditional spill-over and sorting arguments, proximity to other firms enhances foreign trade related activities, provides better flow of information on new market opportunities, offer better transportation and logistics services and supplies workers with higher skills and with the knowledge of foreign languages. From a policy point of view, the results suggest that when evaluating promotion of agglomerated economies or cluster formation, it is important to consider the international activities of participating firms. Producers of non-tradable goods or products that can be sold domestically only might not benefit from these policies to the same degree while firms active in import and export may benefit a great deal more. This also implies that policies promoting the agglomeration of trading firms could be a more specific tool for regional policy.

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6. Appendix

6.1. Descriptives

6.2. Number of firms in the region

So far, we have used employment density as our main explanatory variable, proposing that employment is a good proxy for how likely it is that people can meet and exchange

Table 10: Number of observations

year	all firms	traders
1992	6170	3429
1993	7043	3872
1994	7610	4209
1995	8084	4400
1996	8815	4868
1997	10031	5516
1998	10856	6014
1999	11295	6176
2000	10294	6614
2001	10230	6857
2002	10212	6830
2003	9977	6710

Table 11: Descriptive statistics of main variables.

Variable	Mean	s.d.	s.d. within firm	Min	Max
agglomeration	9.575	1.95	0.11	2.40	12.36
iv1880	0.285	1.24		-1.66	2.04
labor	62.594	293.46	97.17	4.00	13658
capital (ln)	5.096	2.35	0.27	-5.27	16.95
capital / labor	1.798	0.80	0.27	-2.94	9.61
TFP (Levinsohn Petrin)	-0.395	1.23	0.37	-11.51	4.83
TFP (Modified OP)	-1.375	1.54	0.37	-10.28	5.38

ideas. However, as Henderson (2003) argues, firm count may better grasp another aspect of firm-to-firm interactions: commerce and exchange of ideas by management rather than workers. To incorporate this idea, we introduce number of firms as additional controls.

In order to investigate the importance of defining agglomeration in this manner, in Table 12 we use the number of firms instead of employment density. Here, as past density would not properly instrument number of firms, we rely on fixed effects specification. As a first step, we only include the number of firms (in the first two columns). When using the number of firms as an agglomeration measure, we find that non-trading firms also show higher productivity in more dense environments, though the difference as a consequence of the high standard errors is not significant.

There may be several reasons why these two measures would yield different results. First, one could argue that employment density is more directly related to the thickness of the labor market and hence proxies spillovers taking place among employees. Instead, the number of firms approach grasps more the idea of technology spillovers among units of enterprizes. Another difference might stem from the fact that density variable is more sensitive to the presence of large firms than a variable that counts the number of firms.

Table 12: Estimates using number of firms - separate samples FE

	firms trading					
Dep.Var.: TFP	never	always	never	always	never	always
num. firms	0.181**	0.275***				
	[0.0722]	[0.0907]				
num. firms (≥10)			0.0594	0.218**	0.0255	0.123*
			[0.0712]	[0.0838]	[0.0644]	[0.0696]
agglomeration					0.0501	0.145**
					[0.0340]	[0.0558]
size	0.0700***	0.168***	0.0690***	0.168***	0.0693***	0.161***
	[0.0201]	[0.0367]	[0.0203]	[0.0365]	[0.0202]	[0.0356]
foreign ownership	0.0203	0.0756***	0.0202	0.0787***	0.0204	0.0766***
	[0.0165]	[0.0183]	[0.0165]	[0.0182]	[0.0164]	[0.0181]
dummy: year	yes	yes	yes	yes	yes	yes
constant	yes	yes	yes	yes	yes	yes
firm FE	yes	yes	yes	yes	yes	yes
Observations	21958	23063	21950	23062	21950	23062
R-squared	0.022	0.089	0.021	0.089	0.022	0.09
Number of id	5638	3775	5638	3775	5638	3775

Standard errors in parentheses. All use Moulton errors.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Each column shows results from separate regressions. The first and third column use the sample of never trading firms, while the second and fourth that of always traders.

Firm count more closely measures the centrifugal force of competition which is especially true for smaller firms. However, for traders, local market competition should be less important as they partially compete on foreign markets. Competition on factor markets (such as labor and raw materials) remain an issue for all firms. In terms of the empirical investigation, there may be lot of very small firms with very imprecisely measured activity owing to a larger role of the grey economy. Hence, we also estimate separated sample fixed effects regressions for firms with employment size over 10. See column 3 and 4 of Table 12. Results for the regression on the whole sample show a smaller difference between elasticities of traders and non-traders. Focusing on firms with at least 10 employees we found quite different elasticities. This is true when keeping both count and employment in the last two columns. [27]

6.3. The impact of large or multi-site firms

There may be several problems related to large firms possibly operating several sites or at least a separate HQ.

[27] We also carried out several robustness checks on these results using trimmed samples generated by our previously described matching procedure and explicitly leaving out large and small firms. Results remained unchanged.

To see the size of the potential bias when other plants are not within the same micro-region, we can rely on another dataset. This data source comes from the annual labor survey (LFS) that covers all firms with at least 20 employees and a randomly selected set of small firms. In firms with at least 20 employees, one in ten employees is surveyed and the exact location of their workplace is duly noted. We look at this data for all years in our sample. We know from this sample that only 7-8 percent of firms have multiple sites, most multi-plant firms have two plants. On average, firms have 1.15 plants - so this is the maximum size of our bias. As for firms with more than one plant, the largest plant (which, in 80 percent of the cases, is also the site of the firm's headquarters) has 67 percent of the employees.

Table 13: *Within firm share of identified location in matched LFS sample for 2002*

Number of location per firm in LFS	frequency in LFS sample	employment share of the location we identified in our sample / location
1	93%	100%
2	5%	88%
3	1%	78%
4	0.50%	59%
5 or more (avg. values)	0.50%	50%

Location refers to a micro-region

In Table 13 we check the share of employment of a firm in the micro-region that we use as the identifier on the LFS sample. On a 2100 firm sample of 2002, it shows that 93 percent of the firms are within one micro-region. In the case when a firm is located in more than one micro-region, the one that we are able to identify holds 70-90 percent of the firm's employment. Finally, note that these figures mostly refer to firms with above 20 employees, and thus whole economy figures are much smaller, since the majority of firms are small and medium sized enterprizes. This suggests that our biases due to multi-plant firms are probably small: the bias is not larger than 5 percent. This reinforces the notion that headquarters in the case of manufacturing co-locate with the place of production with a higher probability.

6.4. Spatial lag estimation detailed

To control for this possible bias, spatial lag variables of employment and productivity are constructed in the following way. We take the manufacturing population and value added measures summed over the immediate neighboring micro-region and express the total log of total employment in the proximity and productivity as log of total VA per the total employment. Thus each micro-region's immediate neighborhood is accounted for.

$$\text{SL-agglomeration}_{rt} = ln \sum_{it} \mathbf{I} \text{ employment}_{it} \quad (9)$$

$$\text{SL-productivity}_{rt} = ln \frac{\sum_{it} \mathbf{I} \text{ va}_{it}}{\sum_{i} \mathbf{I} \text{ employment}_{it}} \quad (10)$$

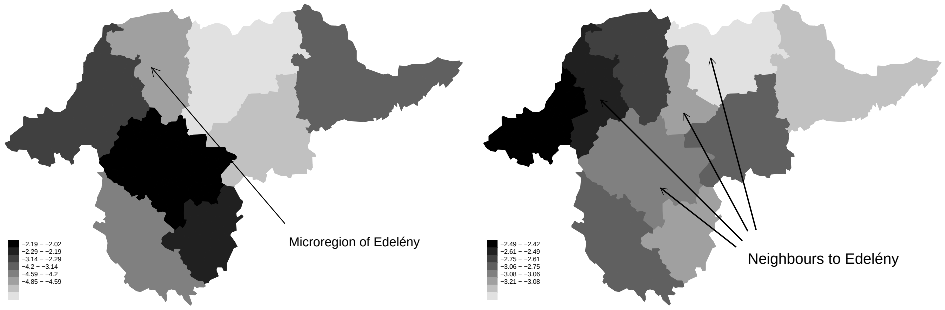
where, va is firm level value added and $\mathbf{I}$ is an indicator function, which takes up value one if a firm is located in the micro-region next to r and SL prefix is used for spatial lag. Adding spatial dependence variables, the specification to be estimated by fixed effects becomes:

$$\begin{aligned} lnTFP_{it} &= \alpha_1 \text{agglomeration}_{rt} + \alpha_{ctrls} \text{controls}_{it} \\ &+ \alpha_{SLA} \text{ SL-agglomeration}_{rt} + \alpha_{SLP} \text{ SL-productivity}_{rt} \\ &+ \upsilon_r + \nu_i + \tau_t + \epsilon_{it} \end{aligned} \quad (11)$$

Figure 1 provides an illustration of the spatial autocorrelation problem and also helps to understand the creation of spatial lag variables (we use SL prefix for spatial lag). On the left side of the figure, one can see the 9 micro-regions of Borsod county colored according to the distribution of manufacturing employment in 1999. Borsod is in the north-east of Hungary, all borderlines to the north are also the national borders with Slovakia. We pick a micro-region, Edelény, as all its neighbors are within Borsod county. As pointed out by the arrow on the left side of the graph, Edelény is surrounded by two very dense regions in the west and south-west. Thus Edelény, though itself not that populated, can actually be considered as part of a broader agglomerated region.

On the right side of Figure 1, the micro-regions of Borsod county are shaded according to the density of their neighbors, the SL variables. Edelény is now more heavily shaded, indicating its proximity to densely populated regions.

Figure 1: Creating SL variables: Example Borsod county densities 1999



(a) agglomeration (b) SL-agglomeration

Panel a) shows the spatial distribution of manufacturing employment (in logs) in Borsod county. Panel b) shows the distribution of manufacturing employment of the neighboring micro-regions calculated for each region (in logs). The darker shades imply higher agglomeration.

Table 14: Agglomeration elasticities by trading activity - separate samples

Dep. Var.: TFP	firms trading	
	never	always
agglomeration	0.0199	0.111***
	[0.0204]	[0.0390]
SL - agglomeration	0.0443	0.0374
	[0.0304]	[0.0406]
SL - productivity	0.00871	0.021
	[0.0197]	[0.0362]
foreign own.	-0.0163	0.411***
	[0.0233]	[0.0307]
instrument:		
ln Pop dens 1880	yes	yes
dummy: sector	yes	yes
dummy: region	yes	yes
dummy: year	yes	yes
First stage: F-stat	45.92	39.13
First stage: R-sq.	0.8644	0.8723
Cragg-Donald Stat.	7291.11	6003.51
Kleibergen-Paap stat.	45.92	39.13
Stock-Wright LM S stat.	0.87	9.59***
F-stat.	129.33	105.94
Observations	25588	23409
R-squared	0.145	0.246

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Moulton corr. standard errors in parentheses

Each column show the results from regression eq.7 on two separate samples of firms: never traders and always traders.

6.5. *Additional Tables*

Table 15: Localization vs urbanization by trading activity - separate samples FE

Dep. Var.: TFP	firms that trade in their time present		
	never	occasionally	always
localization	0.011	0.0354**	0.0370**
	[0.748]	[2.001]	[2.341]
urbanization	0.0345	0.0517	0.0930**
	[1.230]	[1.644]	[2.126]
for	-0.0222	0.00193	0.0727***
	[-1.097]	[0.0874]	[4.690]
dummy: year	yes	yes	yes
constant	yes	yes	yes
Observations	20125	47566	22384
R-squared	0.084	0.092	0.19
Number of id	5288	8110	3671

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moulton corr. standard errors in parentheses

Each column show the results from regression eq.8 on three separate samples of firms: never traders, sometimes or occasionally traders and always traders.

Table 16: Transition matrix for districts agglomeration decile position (1992-2002)

	Starting decile in 1993									
ending decile	1	2	3	4	5	6	7	8	9	10
1	80%	0%	7%	7%	7%					
2	13%	53%	27%		7%					
3	7%	20%	27%	33%		13%				
4		27%	20%	40%	13%					
5			13%	7%	47%	27%	7%			
6				13%	27%	47%	13%			
7			7%			13%	40%	33%	7%	
8							33%	60%	7%	
9							7%	7%	73%	13%
10								0%	13%	87%

Figure 2: Spatial distribution of Manufacturing Productivity 1999

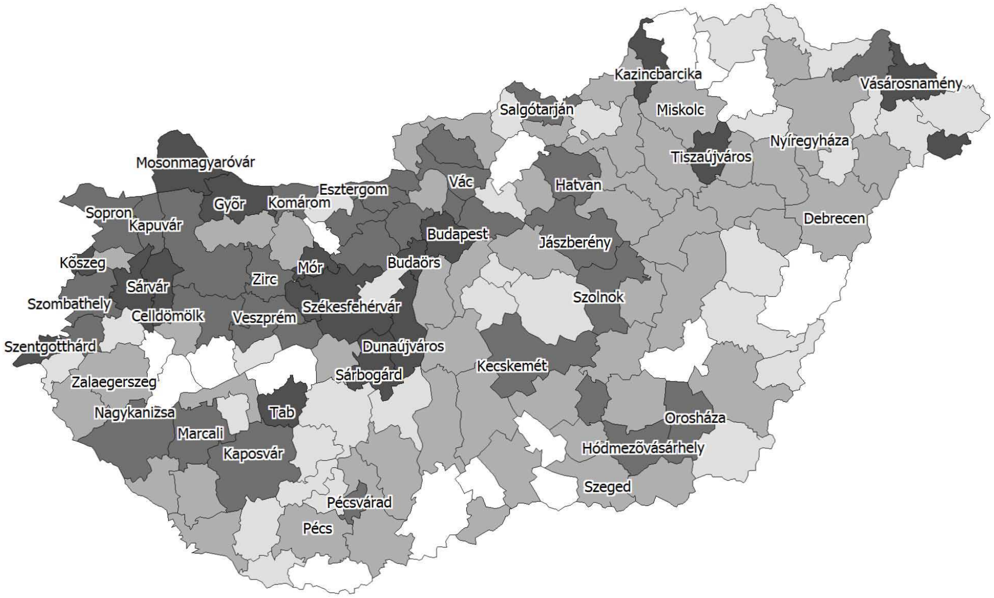


Figure 3: Spatial distribution of Manufacturing Density 1999