Agglomeration economies with consistent productivity estimates

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Abstract

This paper investigates the relative impact of alternative microeconomic agglomeration sources on firm's total factor productivity (TFP) using German establishment and employment level data. Contrasting different strategies to estimate production functions reveals that it is particularly important to account for the endogeneity of input choices and to separate price effects from true productivity. Under the preferred TFP measure, labor market pooling, captured by the correlation of the occupational composition between one county-industry and the rest of the county, is found to have the largest impact. Besides, two knowledge spillover mechanisms, transmitted via job changes and public R&D funding, positively affect firm productivity. I also find that TFP is higher in more specialized and larger counties, whereas sectoral diversity is of no importance.

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1 Introduction

Despite higher factor prices for land and labor economic activity is spatially concentrated[1]. But what exactly makes agglomerations more attractive than sparsely populated regions? More than a hundred years ago, Alfred Marshall (1890) described three motives, why firms locate close to each other: the proximity to their suppliers, a specialized local labor market and the presence of knowledge spillovers. Until today regional scientists are concerned with a thorough examination of these agglomeration forces. Over the last two decades researchers have developed different microeconomic foundations for Marshall's anecdotal evidence[2]. A lot of these models predict that input linkages, labor market pooling and knowledge spillovers manifest in higher productivity, which is ultimately a reason, why firms are better off in agglomerations[3]. Yet, concerning the empirical evidence, Glaeser and Gottlieb (2009: 985) note that "the field has still not reached a consensus on the relative importance of different sources of agglomeration economies".

The few studies that are concerned with the assessment of their relative importance differ largely in the dependent variable at use. Puga (2010: 204) argues that productivity is the most direct measure in order to capture agglomeration economies. In fact, examining employment growth or concentration may suggest that Marshall's forces are beneficial to firms. Yet, these approaches are silent about the exact nature of the benefit. Looking at firm productivity allows us to shed more light into this black box[4].

The present study seeks to answer the following two unresolved issues. Do these Marshallian agglomeration forces actually lead to a higher firm productivity as theory tells us? Which of them is empirically more important? To this end a total of six agglomeration variables for labor pooling, input relations and knowledge spillovers are constructed, following closely the predictions from theoretical models. Different TFP estimates from plant level production functions are then regressed on these agglomeration proxies. The present paper also adds to the ongoing debate about what kind of sectoral environment is most

[1]For evidence from elaborated concentration indices see Duranton and Overman (2005) for the UK and Koh and Riedel (2009) for Germany.

[2]Duranton and Puga (2004) provide a comprehensive survey of this literature.

[3]Of course, firms base their location choice on expected profits rather than on expected productivity. Therefore besides TFP differences cost advantages or higher demand in agglomerations may coexist, but these influences are much harder to trace than TFP.

[4]In this context Cingano and Schivardi (2004) compare regressions with TFP growth and employment growth as dependent variable. They even find opposite results in both cases with respect to the size and specialization of a region.

beneficial to firms (Beaudry and Schiffauerova 2009). I test several proxies for localization and urbanization economies for their impact on TFP. Moreover, the investigation is not restricted to the manufacturing sector.

Discriminating between different forces is complicated due to their 'Marshallian equivalence' (Duranton and Puga 2004). That is, most theoretical models on agglomeration mechanisms share the prediction that the benefits grow in the number of workers or firms. Indeed, earlier contributions have used the size (Sveikauskas 1975) or density of areas (Ciccone and Hall 1996) as proxies. Though these are interesting questions, it remains unclear how the agglomeration benefits are actually transmitted to firms. Another advancement from the examination of micro-founded agglomeration mechanisms is that the source of externalities is not bound to a single industry or the city as a whole. The way I construct the agglomeration variables, considers an interplay between different industries, depending on their size and similarity.

Presumably due to data constraints, only a small fraction of studies draws inference from TFP[5]. The majority of those that do, e.g. Henderson (2003), Combes *et al.* (2010), look at measures of concentration and urbanization economies but not at agglomeration mechanisms. There are two exceptions that relate several agglomeration mechanisms to productivity. Greenstone *et al.* (2010) provide evidence that each Marshallian force separately leads to a higher TFP, however they fail to do so in a multivariate setting. Of course, just in the latter case can we compare their relevance. Rigby and Essletzbichler (2002) find that all three Marshallian forces simultaneously have a positive effect on labor productivity. Still the study does not compare their magnitude and as will be clear below, I argue that labor productivity is not a particularly reliable measure.

In further contrast to earlier contributions, I devote considerable attention to the estimation of total factor productivity (TFP) from firm level production functions. In order to quantify the gains from agglomeration economies, a correct TFP estimate is an essential requirement. I account for the correlation of input choices with current productivity levels using the Olley and Pakes (1996) procedure. Furthermore, I correct for unobserved output prices as proposed in Klette and Griliches (1996), which allows one to separate true productivity from demand side effects. It will be shown that the estimation technique makes a difference with regard to the significance level and magnitude of ag-

[5]See Rosenthal and Strange (2004), Puga (2010) and Glaeser and Gottlieb (2009) for surveys on the empirics of agglomeration economies.

glomeration mechanisms. So far only De Loecker (forthcoming), Del Gatto *et al.* (2008) and Muendler (2007) have corrected jointly for the simultaneity bias and the omitted price bias, but none of them has taken the TFP estimates into spatial analysis.

Using establishment and employment level data from the Institute for Employment Research (IAB) from 2000 to 2005, I find that in univariate regressions all agglomeration mechanism variables have the expected sign and statistical significance. However, some variables' significance vanishes in multivariate regressions. Labor pooling, captured trough the correlation of the occupational composition between one county-industry and the rest of the county, is found to have highest and most significant impact on firm productivity. Besides, two knowledge spillover mechanisms, transmitted via job changes and public R&D funding, positively affect firm TFP. The poor performance of input linkages may be due to the lack of detailed information about the flow of intermediate goods. Probably the most informative study on this topic is Ellison *et al.* (2010), where the authors find that all three Marshallian forces exert positive influence on the co-agglomeration of similar industries, with input-output relations being the most important[6]. In both multivariate and univariate regressions the results tend to be more significant and higher in magnitude, when the omitted price and endogeneity bias are accounted for. On the one hand, it confirms the theoretical (Melitz 2003) and empirical (Foster *et al.* 2008) finding that highly productive establishments set lower prices. Which, on the other hand, stresses the importance of separating price effects from true productivity. As robustness checks I construct four additional productivity measures: labor productivity, TFP estimated from value added instead of revenue based production functions, and TFP resulting from the Levinsohn and Petrin (2003) and the Ackerberg *et al.* (2006) estimation procedure as alternatives to the Olley and Pakes (1996) model. I find the main conclusions to remain valid under these extensions. The comparison suggests that value added based TFP and especially labor productivity are likely to overestimate the size and significance of agglomeration variables. Concerning the discussion about externalities from the industrial environment, no significant sign is found for a diversified industrial structure, as suggested by Jane Jacobs (1969). But the data suggests that localization proxies are beneficial to firm's productivity. Average productivity is higher by about 2-3 percentage points, when the employment size of

[6]The different outcome here is astonishing because the construction of the labor pooling and input relations variable are quite similar.

a region is doubled. This result is within the range of previous studies from other countries that also draw inference from TFP, e.g. Henderson (2003) and Combes *et al.* (2010).

The remainder of the paper is organized as follows. The next section lays out the estimation strategy. Section 3 describes the data and the construction of the agglomeration variables. Estimation results are presented in section 4. Section 5 provides some robustness checks and section 6 concludes the paper.

2 TFP estimation

Before presenting the estimation strategy used in the paper, this section reviews some of the difficulties in estimating production functions. Subsequently, I describe, how they are incorporated in order to obtain a consistent productivity measure. Starting point is the standard Cobb-Douglas technology in logarithmic form

$$y_{jt} = a_{jt} + \alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_m m_{jt} + \zeta z_{jt} + u^p_{jt} \tag{1}$$

where y_{jt} is output of firm j in period t, α_x with $x = \{k, l, m\}$ is the elasticity of capital, labor and intermediate inputs, and u^p_{jt} is an unobserved i.i.d. shock to production. The term z_{jt} represents controls in the production function, which are a dummy variable for firms located in West Germany, industry fixed effects and the firm's share of high skilled workers. Total factor productivity a_{jt} can be split up in two terms: $a_{jt} = \beta_0 + \omega_{jt}$. The first one, β_0, can be interpreted as common stock of technology or an efficiency level shared by all firms. ω_{jt} is the firm specific part of TFP[7], being unobserved by the researcher but known to firm.

Two well known problems plague the estimation of production functions: the transmission bias and the omitted price bias. The first problem arises, because the current productivity level influences the decision about optimal input usage[8]. Klette and Griliches (1996) prove that the direction of the transmission bias is strictly positive. Thus when adjusting for this bias, we expect lower scale elasticity estimates. Several strategies have been proposed to overcome this problem[9]. One of the most prominent is the control function

[7]Henceforth the terms TFP and likewise productivity only refer to this firm specific part ω_{jt}, unless explicitly stated.

[8]Deriving optimal input demand functions from (1) proves their positive dependence on productivity.

[9]cf. Ackerberg *et al.* (2007) or Eberhardt and Helmers (2010) for a comprehensive survey.

approach from Olley and Pakes (1996), which will be applied here. The basic idea behind the control function approach is to find a firm's decision variable that depends on productivity. The inversion of this function allows us to replace the unknown ω_{jt} from the production function. Possible candidates for this decision variable are investments, marketing expenditures or intermediate inputs.

The omitted price bias arises due to the fact that in theory the LHS variable in the production function is output measured in quantities. Unfortunately there are only few data sets, where this information is given. Usually firms report their output in monetary units, which means that the firm's log price p_{jt} has to be added to both sides of equation (1). Prior studies have typically proxied p_{jt} by an industry level deflator or have completely ignored the problem. If firm prices were to depart systematically from the average price level of the industry, regression coefficients will be biased. Theoretical models featuring firm heterogeneity like Melitz (2003) tell us, that the most productive firms will quote below average prices, sell above average quantities and consequently use more of the production factors. Hence downward biased regression coefficients can be expected from estimation of equation (1)[10]. Foster *et al.* (2008) make use of a dataset with information on output in physical quantities and revenues, confirming that revenue based productivity estimates embody price variation. Consequently, inference from revenue based and physical productivity estimates is different. When presenting the estimation results, I will also discuss the outcomes without adjustments for the endogeneity and omitted price bias.

2.1 Identification strategy

This section outlines how the two presented biases are taken into account, in order to derive consistent TFP estimates. At first I make use of a specific demand system to tackle the omitted price bias. Then a model of industry dynamics is introduced, which allows to implement the control function for unobserved TFP. De Loecker (forthcoming), Del Gatto *et al.* (2008) and Muendler (2007) have already combined these two estimation procedures from Klette and Griliches (1996) and Olley and Pakes (1996) (OP henceforth). The main novelty here is the application to a regional data and consequently allowing the productivity variable to be influenced by some agglomeration variables

[10] Klette and Griliches (1996) also discuss other influence channels that lead to a systematic negative relation between prices and input factors.

G^k. Furthermore, I also control for an additional selection bias, as proposed in the original OP framework but not adopted by the above cited studies.

It is now clear that the production function with output in terms of log revenue r_{jt} in fact looks like this

$$r_{jt} = y_{jt} + p_{jt} = a_{jt} + \alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_m m_{jt} + \zeta z_{jt} + u_{jt}^p + p_{jt} \tag{2}$$

To replace unobserved firm level prices p_{jt}, I rely on the CES demand function from the Dixit and Stiglitz (1977) framework. The logarithmic form is

$$q_{jt} = -\sigma\left(p_{jt} - p_{It}\right) + q_{It} + u_{jt}^d \tag{3}$$

where firm level demand q_{jt} depends negatively on the firm's own price and positively on an aggregate demand shifter q_{It} and an aggregate price index q_{It}. σ is the constant elasticity of demand and u_{jt}^d are i.i.d. demand shocks.

When it comes to the empirical implementation, the question is, what is the relevant market for a firms. Two arguments suggest that the industry segment of the national market is a reasonable approximation: (1) Given that the majority of exporting firms generate only a small percentage of their revenues abroad (Fryges and Wagner 2010), for most firms the national market is what matters. (2) Economic conditions on input and sales markets in all sectors implausibly follow the same development over time. So taking one and the same price index and demand shifter for all firms, seems a rather crude proxy. To make the distinction between sectors clear, p_{It}, q_{It} and σ get the superscript 's' henceforth. Combining demand side information from (3) with the production function in (2) yields

$$\begin{aligned}\widetilde{r}_{jt} &:= y_{jt} + p_{jt} - p_{It} = \\ &= \left(\frac{\sigma^s - 1}{\sigma^s}\right)\left(a_{jt} + \alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_m m_{jt} + \zeta z_{jt}\right) + \frac{1}{\sigma^s}\left(r_{It}^s - p_{It}^s\right) + u_{jt}\end{aligned} \tag{4}$$

Both i.i.d. shocks u_{jt}^d and u_{jt}^p are combined in u_{jt}. Estimating this production function with deflated revenues as the dependent variable circumvents the omitted price bias, while it also provides an estimate for the demand elasticity in industry s as a byproduct. Note that productivity $\widetilde{a}_{jt} \equiv \widetilde{\beta}_0 + \widetilde{\omega}_{jt} = (\frac{\sigma^s-1}{\sigma^s})(\beta_0 + \omega_{jt})$ and the input elasticities $\widetilde{\alpha}_x \equiv (\frac{\sigma^s-1}{\sigma^s})\alpha_x$ with $x = \{K, L, M\}$ are reduced form parameters, when estimated without adjustment for the omitted price bias.

Now, ω_{jt} is the only remaining unobserved factor hindering consistent estimation of the production function. Following Olley and Pakes (1996) I introduce a model of firm behavior, which builds on the following assumptions. Firm specific productivity follows an exogenous first order Markov process

$$\omega_{jt} = E[\omega_{jt}|\mathfrak{I}_{t-1}] + \xi_{jt} = f(\omega_{jt-1}) + \xi_{jt} \tag{5}$$

where $\mathfrak{I}_{t-1}$ is the information set in period $t-1$, f is a function that describes the conditional expectation of ω_{jt}, and ξ_{jt} is the innovation shock in the Markov process. Furthermore, there is a certain timing in the choice of input factors. Labor and material are non-dynamic inputs, i.e. they are chosen in the beginning of the actual period. Capital evolves according to the investments I_{jt-1}[11] taken in the preceding period and the existing capital stock in $t-1$ less of depreciation

$$K_{jt} = (1-\delta_{jt-1})K_{jt-1} + I_{jt-1} \tag{6}$$

where δ_{jt-1} is the firm specific depreciation rate. Next, a Bellman function can be set up and solved, cf. Olley and Pakes (1996) for details. This yields two important equations. Firstly, an exit rule, predicting that a firm will continue its operation ($\chi_{jt} = 1$), if the current productivity is above a certain threshold.

$$\chi_{jt} = \begin{cases} 1 & \text{if } \omega_{jt}(G_t^k) \geq \bar{\omega}_t(k_{jt}, G_t^k) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Given that the profit function is increasing in capital, this firm specific threshold $\bar{\omega}_t(k_{jt}, G_t^k)$ is negatively correlated with capital. In other words, from two firms which face the same productivity shock ω_{jt}, the one with the greater capital stock is less likely forced out of the market[12]. Productivity and the productivity threshold are allowed to be influenced by other factors in a region k, summarized in G_t^k.

Secondly an investment demand equation $i_{jt} = i_t(k_{jt}, \omega_{jt}(G_t^k))$ is derived from the solution of the Markov perfect Nash equilibrium of the underlying OP model. Given that investment demand is monotonic in ω_{jt} and the regional fac-

[11]Note that large case letters denote variables in levels and lower case letters always denote log variables here, e.g. $log(I_{jt}) = i_{jt}$.

[12]The dataset lends support to this assumption. When the sample is split up into firms that survive and those that exit the market, the latter group has on average a lower capital stock, both in time average and especially in the last period prior to exit. However, exiting firms only comprise about 4% of all firms, which is why the selection bias will presumably be small.

tors are known exogenous state variables, inversion gives $\omega_{jt} = h_t(k_{jt}, i_{jt}, G_t^k)$. The upper panel in figure 1 in the appendix provides a graphical assessment for the latter assumption. The figure plots investments against a third order polynomial in k_{jt} and TFP (from the preferred OP/KG estimation). The surface is increasing in the productivity axis and only slightly decreasing at the upper end, suggesting that the invertability condition is likely to be satisfied. This function $h_t(k_{jt}, i_{jt}, G_t^k)$ is finally the control function that will be used to replace unobserved productivity in the production function.

$$\widetilde{r}_{jt} = \widetilde{\beta}_0 + \widetilde{h}_t(k_{jt}, i_{jt}, G_t^k) + \widetilde{\alpha}_k k_{jt} + \widetilde{\alpha}_l l_{jt} + \widetilde{\alpha}_m m_{jt} + \frac{1}{\sigma^s}(r_{It}^s - p_{It}^s) + \zeta z_{jt} + u_{jt}$$

$\widetilde{h}_t$ is still an unknown function but in known variables. It is possible to approximate this function by a polynomial in k_{jt}, i_{jt}, G_t^k. Due to multicollinearity problems with this polynomial, $\widetilde{\beta}_0$ and $\widetilde{\alpha}_k$ can not be identified[13]. Estimation of the production function is therefore divided into two stages.

$$\widetilde{r}_{jt} = \widetilde{\beta}_0 + \widetilde{\alpha}_l l_{jt} + \widetilde{\alpha}_m m_{jt} + \frac{1}{\sigma^s}(r_{It}^s - p_{It}^s) + \phi_t(k_{jt}, i_{jt}, G_t^k) + \zeta z_{jt} + u_{jt} \quad (8)$$

is the first stage estimating equation yielding the coefficients $\hat{\sigma}^s, \hat{\widetilde{\alpha}}_l$ and $\hat{\widetilde{\alpha}}_m$. The unknown function $\phi_t(k_{jt}, i_{jt}, G_t^k) = \widetilde{\alpha}_k k_{jt} + \widetilde{h}_t(k_{jt}, i_{jt}, G_t^k)$ is approximated by a second order polynomial. With the estimates $\hat{\sigma}^s$, $\hat{\widetilde{\alpha}}_l$ and $\hat{\widetilde{\alpha}}_m$ at hand, the production function can be rewritten as

$$\widetilde{r}_{jt}^* := \widetilde{r}_{jt} - \hat{\widetilde{\alpha}}_l l_{jt} - \hat{\widetilde{\alpha}}_m m_{jt} - \left(\hat{\frac{1}{\sigma^s}}\right)(r_{It}^s - p_{It}^s) - \hat{\zeta} z_{jt} = \widetilde{\beta}_0 + \widetilde{\alpha}_k k_{jt} + \widetilde{\omega}_{jt} + u_{jt} \quad (9)$$

Two advantages of the first stage estimation are now visible: (1) we already have consistent estimates of $\widetilde{\alpha}_l$ and $\widetilde{\alpha}_m$, since ω_{jt} was completely proxied by ϕ_t. (2) From the first stage we now have an estimate for productivity $\hat{\omega}_{jt} = \hat{\phi}_{jt} - \widetilde{\alpha}_k k_{jt}$. This time we avoid the multicollinearity concerning k_{jt} by use of equation (5) in (9)

$$\widetilde{r}_{jt}^* = \widetilde{\beta}_0 + \widetilde{\alpha}_k k_{jt} + \widetilde{f}(\omega_{jt-1}(\cdot)) + \xi_{jt} + u_{jt} \quad (10)$$

Because firms have knowledge about ω_{jt-1}, but do not expect the innovation shock ξ_{jt}, the choice of k_{jt}, which is completely determined in $t-1$, can not be correlated with the unobserved ξ_{jt}. That is, the following moment condition

[13] Note that the polynomial $\widetilde{h}_t$ also contains a constant, and k_{jt} appears twice, linear from the original production function and in $\widetilde{h}_t$. Therefore k_{jt} is combined with $\widetilde{h}_t$ into ϕh_t.

holds: $E[\xi_{jt}|k_{jt}] = 0$.

Yet, a third problem troubles the consistent identification of the capital coefficient, as inspection of (7) makes clear. We argued above that the productivity threshold $\bar{\omega}_t$ is falling in k_{jt}. In unbalanced panel data sets selection will therefore lead to a negative correlation between productivity and the capital stock of firms remaining in the panel. This selection bias can be controlled for, by taking the conditional expectation of the production function in equation (10) on being in the market in period t and the information firms have in $t-1$

$$\begin{aligned}
E[\widetilde{r}^*_{jt}|\mathfrak{I}_{t-1}, \chi_{jt} = 1] &= \widetilde{\beta}_0 + \widetilde{\alpha} k_{jt} + E[\widetilde{\omega}_{jt}|\mathfrak{I}_{t-1}, \chi_{jt} = 1] \\
&= \widetilde{\beta}_0 + \widetilde{\alpha} k_{jt} + E[\widetilde{\omega}_{jt}|\mathfrak{I}_{t-1}, \omega_{jt} \geq \bar{\omega}_t(k_{jt}, G^k_t)] \\
&= \widetilde{\beta}_0 + \widetilde{\alpha} k_{jt} + \widetilde{g}(\omega_{jt-1}, \bar{\omega}_t(k_{jt}, G^k_t))
\end{aligned}$$

In the second line the exit condition from (7) is made explicit, and the third line follows from the law of motion of ω_{jt} and the definition of conditional expectation for a continuous variable. The survival probability $Pr_{jt} = \Pr(\chi_{jt} = 1|\mathfrak{I}_{t-1})$ can be written as

$$\begin{aligned}
Pr_{jt} &= \Pr(\omega_{jt-1}(i_{jt-1}, k_{jt-1}, G^k_{t-1}), \bar{\omega}_t(k_{jt}, G^k_t)|\mathfrak{I}_{t-1}) \\
&= \widetilde{\varphi}_t(\omega_{jt-1}(\cdot), \bar{\omega}_t) = \varphi_t(i_{jt-1}, k_{jt-1}, G^k_{t-1})
\end{aligned} \tag{11}$$

This transformation uses equation (6), but it also implies that the regional characteristics G^k_t are temporally autocorrelated. Pr_{jt} is estimated in a separate Probit Model, where the unknown function φ_t is approximated by a second order polynomial in its arguments. Inversion of equation (11) gives $\bar{\omega}_t = \widetilde{\varphi}^{-1}(\omega_{jt-1}, Pr_{jt})$, provided that the density of ω_{jt} conditional on $\mathfrak{I}_{t-1}$ is positive around the value $\bar{\omega}_t$. This inverted function is used modified productivity process respecting market selection

$$\omega_{jt} = E[\omega_{jt}|I_{t-1}, \chi_{jt} = 1] + \xi_{jt} = \widetilde{f}(\omega_{jt-1}, Pr_{jt}) + \xi_{jt}$$

Identification of k_{jt} is based on the moment condition $E[\xi_{jt}|k_{jt}] = 0$ derived above. The consequence of controlling for selection is that candidate values for ξ_{jt} are taken from non-parametrical regression of $\omega_{jt}(\widetilde{\alpha}_k)$ on $\omega_{jt-1}(\widetilde{\alpha}_k)$ *and* Pr_{jt}, where the estimates $\hat{\omega}_{jt}(\widetilde{\alpha}_k) = \hat{\phi}_{jt-1} - \widetilde{\alpha}_k k_{jt-1}$ are available from the first stage estimation. Though the derivation is cumbersome, the intuition behind the adjustment for the selection bias is quite clear: To control for endogenous market selection of firms with low capital stock, the survival probability has to enter the identification equation. Essentially, the second stage is the minimization of the sample analogue to the above population moment

$$\frac{1}{T}\frac{1}{N}\sum_{t}\sum_{j}\hat{\xi}_{jt}(\widetilde{\alpha}_k)\cdot k_{jt} \tag{12}$$

Finally log composite TFP is residually collected from

$$\hat{a}_{jt} = \left[\widetilde{r}_{jt} - \hat{\widetilde{\alpha}}_l l_{jt} - \hat{\widetilde{\alpha}}_m m_{jt} - \hat{\widetilde{\alpha}}_k k_{jt} - \left(\widehat{\frac{1}{\sigma^s}}\right)(r_{It} - p_{It}) - \hat{\zeta} z_{jt}\right]\left(\frac{\hat{\sigma^s}}{\hat{\sigma^s} - 1}\right)$$

Note that the true firm specific part of TFP ω_{jt} is not identified, because the procedure does not yield a consistent estimate of β_0.

3 Data

3.1 Establishment data

For the estimation of the production functions the IAB Establishment Panel (IABB) is used from 2000 to 2007. It is a representative sample from the population of all German firms with at least one employee liable to social security. Around 16.000 establishments per year are drawn according to the principle of optimal stratification along a division into 17 industries and 10 plant size classes. In personal interviews plant managers are questioned about the employment structure, revenues, investments and the organizational structure. The main advantage of this panel is that the location of the plant at NUTS 3-digit level (counties) and the industry classification are also available. A more detailed description of the IABB is given in Fischer *et al.* (2009).

The following information is extracted from the IABB. Intermediate inputs comprise all materials, intermediate goods and services purchased from other plants. Labor input is the number of all workers on June 30th in each period. From information about their qualification level I construct the share of skilled workers as a control for the quality of the labor input. Skilled workers span candidates for civil service, working proprietors and employees who have completed an apprenticeship or hold a university degree. Another control in all production functions is a dummy indicating, if an establishment is located in West-Germany. The literature concords, that until the present day, East and West German firms are considerably different from each other.

Unfortunately no balance sheet information about the value of capital is reported in the IABB. Therefore, the capital variable is constructed from plant investment behavior employing the modified perpetual inventory method according to Müller (2008). His approach differs from the usual perpetual inventory method (PIM) in the construction of the starting value. At first, one has to calculate average economic lives of the industry level capital stock from the national accounts[14]. The modified PIM proceeds with two assumptions: (1) the depreciation rate δ_t^I is linear, i.e. it is equal to the reciprocal of the average economic live of the capital stock. (2) All firms within an industry share the same depreciation rate. The latter assumption is necessary, because the observation period of firms in the IABB is not long enough to derive reasonable depreciation rates from their reported investment behavior. Another reason is that the type but not the amount for each type of investment is reported. A starting value for the modified PIM is approximated by the time-mean of replacement investments over the industry specific depreciation rate. In all subsequent periods the usual perpetual inventory method is applied according to equation (6) assumed in the Olley and Pakes (1996) model. The only difference lies in the industry specific depreciation rate δ_t^I.

Difficulties in the application of the PIM arise, when changes in plant size occur. The IABB questionnaire asks each plant, if it sold, spun off or shut down parts of the plant, or if the plant integrated new parts. Clearly, these changes have implications for the capital stock of the firm. For some firm that has just sold a part of its assets, the PIM will overstate its capital value in the following periods. Therefore, whenever such change occurred, the plant is treated as a new plant that has just entered the panel, and the PIM is restarted[15]. To make sure that the observation periods do not become very shot, all plants with two or more organizational changes are excluded from the sample. For the proper application of the PIM establishments with less than three valid observations are also dropped.

Another difficulty arises from the industrial classification systems in Germany. Since the first IABB survey in 1993, the official industrial classification (WZ) from the German Federal Statistical Office (FSO) has changed in 1993 and 2003. However, the IABB has been using two distinct classification schemes. One of them is composed of the 17 industries from the stratification matrix mentioned above. The other one appears in the questionnaire, where managers are asked to classify their core economic activity into one of 41 dif-

[14]The values for average economic lives of the equipments (12 years) and buildings (58 years) are adopted from Wagner (2010).

[15]In this adjustment I depart from the modified PIM outlined in Müller (2008).

ferent industries. These 41 industries accord with industries from either the WZ 1-digit or 2-digit level. Until 1999 these two IABB classification schemes were aligned to the former official WZ73 system and from 2000-2003 to the WZ93. Only since 2004 the IABB's industrial classifications accord with the current FSO classification WZ2003[16]. The shift from WZ93 to WZ2003 left the 41 questionnaire industries unaffected, because changes took place only within subgroups below the 2-digit level. However, the sizable rearrangement in the year 2000 limits longitudinal comparisons across industries (Fischer *et al.* 2009). Correct industrial classification is required out of four reasons: (1) as a control in the production function, (2) to construct the agglomeration variables, (3) to distinguish the agglomeration effects across industry groups, (4) to enrich the firm level data with external industry specific information, as explained momentarily; To avoid any errors through the imputation in the sector variable, the present study is restricted to observations after the year 1999.

3.2 Industry data

As was made clear from the description of the estimation strategy above, the production function is combined with a specific demand system in order to replace unobserved firm prices by aggregate demand shifters and price indices. Since I have assumed that the relevant market is industry specific, aggregate revenues are an appropriate demand shifter. The necessary data is taken from the Federal Statistical Office. Unfortunately in most of the service industries these statistics were not collected before the year 2005. Because this external information is crucial for the estimation procedure, no use of such industries could be made. Table 1 lists the 22 remaining industries and the respective number of observations without any missing values in all variables.

In five of the 22 industries that are used, no information on total sales was available. In these cases, sales are projected from the IABB sample[17]. The German FSO calculates producer price indices according to the Laspeyres

[16]The German WZ2003 classification is based on the European general classification of economic activities NACE (NACE) Rev. 1.1.

[17]The IABB sample provides cross sectional and longitudinal weighting factors for all firms with valid observations. These weighting factors are computed in a manner that allows inference to the population. Projections are valid in the two dimensions of the stratification matrix: industries and classes of firm size (Fischer *et al.* 2009). Luckily the five industries without total sales accord with the industries in the stratification matrix. Only for the construction industry this was not exactly the case. In the 41 questionnaire industries it is partitioned into main construction trade and construction installation. For the main construction trade aggregate information on total sales is given, so that revenue in the construction installation is residually computed.

Table 1: overview of industries

group	industry name	obs.
high-tech [1]	machinery and equipment	1558
	motor vehicles	219
	other transport equipment	60
	electrical machinery	708
	precision and optical instruments	306
medium-tech [2]	chemical products, coke and refined petroleum products	571
	rubber and plastic products	582
	non-metallic mineral products	513
	basic metals	453
	fabricated metal products	1010
low-tech [3]	food, beverages and tobacco	866
	textile, apparel and leather	274
	pulp, paper and printing	387
	wood products	334
	furniture	210
non-manufacturing [4]	agriculture, forestry and fishing	847
	mining & quarrying, electricity, gas and water supply	574
	main construction trade	1376
	construction installation	1517
	hotels and restaurants	676
	transport, storage and communication	1177
	wholesale and retail trade	3657

formula, which is the sum of product prices weighted by their share total domestic revenue. This accords well with the assumption on the relevant market. The weighting scheme is not adjusted every year in order to separate price changes from quantity effects. 2005 is the current base year, which means that all price indices were normalized to 100 in 2005. In the non-manufacturing sectors 'hotels and restaurants', 'transport, storage and communication' and 'wholesale and retail trade' the FSO has started to collect service prices from the suppliers only since 2007. For these industries consumer price indices are used instead.

3.3 Regional data

It is clear that the strength of agglomeration economies decays with distance. However, the spatial sphere of influence may differ across the agglomeration channels. For example, a labor market advantage, based on the mobility of workers, is likely to extend over a larger geographical area than knowledge spillovers created through the incidental meeting of workers. I opted to take counties (the NUTS 3-digit level) as spatial reference points, which can be regarded as a compromise between larger labor market regions and the city level. In 2007, Germany was divided into 423 counties[18]. Most of the information to construct agglomeration variables is taken from other datasets (as detailed below) and is then matched into the IABB via the industrial and spatial classifications.

3.3.1 Urbanization and localization

The FSO provides the square footage and the number of employees in each county for the 22 industries examined in this study. Furthermore the total employment level in each county is taken from the Federal Employment Agency (BA). Based on this information the urbanization and localization variables are constructed as follows. Localization economies (or interchangeably specialization economies) are captured through the employment share of industry i in county k: $\frac{E_i^k}{E^k} = \frac{E_i^k}{\sum_i E_i^k}$. In order to investigate, whether the absolute or the relative size of an industry is more important, I also experiment with the employment level in a county-industry.

The urbanization hypothesis, often associated with the work of Jacobs (1969), predicts that a diverse industrial environment will foster productivity of all firms in that region. The construction of a diversity measure is not straightforward. Henderson (2003) used a comparison between the industrial structure of a county k and the whole country

$$jacobs1^k = \sum_i \left(\frac{E_i^k}{E^k} - \frac{E_i}{E} \right)^2$$

where E_i is total employment in industry i and $E = \sum_i E_i$ is the total of workers in Germany[19]. If the employment shares of all industries i in a county mirror the national employment shares, this measure takes on the value of zero. In this case county k possesses the maximum diversity. In fact, $jacobs1$ measures the lack of diversity, hence the urbanization hypothesis predicts a negative coefficient. A second inverse measure of diversity ($jacobs2$) used is the

[18]All districts that have undergone changes between 2000 and 2007 are aggregated, so that the area is consistent throughout these year. This is the case for districts in Saxony, the city of Hannover and Berlin.

[19]Note that all terms in the construction of $jacobs1^k$ vary by time, but are not explicitly denoted by a subscript t to save on notation. This applies also in the construction of the following agglomeration variables.

employment share of the three largest industries in a county[20]. For comparisons with earlier studies, e.g. Combes *et al.* (2010) and Ciccone and Hall (1996), the log density and the log size (in terms of employment) of a region will also be employed in the productivity analysis.

Even though all of these regional variables capture agglomeration economies, they do not provide us with a notion of how productivity benefits are actually transmitted to firms. Duranton and Puga (2004) survey a wide range of models which provide different microeconomic foundations of agglomeration economics. All of them share the same prediction: large locations are beneficial to firms. The challenge for empirical work is to discriminate between them. Since most of the models are based on two types of labor and only one or two sectors, some interpretation is necessary for the empirical implementation. Yet, I tried to align the variables' construction as closely as possible to the underlying theory. In the center of attention of this investigation are the following microeconomic mechanisms, classified according to the famous three Marshallian labels.

3.3.2 Input-relations

Models with an intermediate goods sector, e.g. Ethier (1982), Abdel-Rahman and Fujita (1990), predict that an increasing number of intermediate goods producers will raise productivity of firms in the final goods sector. These models typically assume that all assembling firms use all available intermediate goods. When we take this prediction to the empirical inquiry, we may want to be more realistic. In fact, some industries are heavily dependent on inputs from another industry or even from their own industry, while other sectors hardly exchange goods. Usually researchers have looked at both input and output linkages. In order to stick as close as possible to the underlying theory, only input flows are considered here. Introducing trade costs, as e.g. in Venables (1996), implies higher demand for local intermediate goods and in turn a higher contribution to the productivity of their local customers. For simplicity this investigation disregards interactions with neighboring counties and focuses only on supplier relations within the own county.

The indicator for supplier relations in industry i is the amount of goods that

[20]Glaeser *et al.* (1992) have used the share of the five largest industries in a city to capture Jacobs economies. Note that in the construction of $jacobs2$ only the 22 sectors considered in this investigation form the total county employment. This explains its large mean of 0.58, cf. table 2 below.

industry i purchases from industry j relative to all industry i's inputs[21]. Intra-industry transactions are considered as well. Because the range of industries are relatively broad, it is not surprising that intra-industry input shares are on average much larger than shares between different industries. These numbers provided by the FSO in the input-output-matrix, are used to construct the following indicator for the strength of input-output-relations. Regarding supplier relations within an industry, basic metals (0.64), chemical industry (0.57) and motor vehicles (0.48) rank on top. Between different industries the highest share of input usage is observed for sales from transportation/communication to wholesale/retail trade (0.33). Then this measure of linkage strength between industry i and all other industries j $strength_{ij}$ is related to the industrial structure in each region as follows

$$input\text{-}linkage_i^k = \sum_j \left(strength_{ij} \cdot \frac{E_j^k}{E^k} \right)$$

According to the theory outlined above, this means that in every county input-externalities rise in the relative size of the supplying sector.

3.3.3 Labor market pooling

One interpretation of labor market pooling in Coles and Smith (1998) is based on a frictionless labor market, where firms post their vacancies and unmatched workers apply for all of these posts. The demand side has perfect information about the quality of applicants. If a firm finds an adequate candidate a match occurs, yet not necessarily all agents will be matched. This framework generates a matching function with increasing returns to scale in both the number of firms and workers. That means a larger market provides more opportunities to find suitable matches and thus expected productivity is higher. For the empirical realization I compute the correlation between occupations in the industry under scrutiny and all remaining occupations in a county. This construction presumes that all firms from the same industry in a county have a common composition of staff. The closer the industry profile is to the composition of the local labor market, the less effort firms from that industry have in finding suitable employees. In this manner the variable is also close to the original

[21] Note that the normalization for the supplier measure is done with the amount of inputs from all industries. Ellison *et al.* (2010) use a similar measure for input-relations, but their investigation is about the coagglomeration of industries and does not consider spatial differences.

writing of Marshall (1890: 271): "a localized industry gains great advantage from the fact that it offers a constant market for skill. Employers are apt to resort to any place where they are likely to find a good choice of workers with special skill which they require". The information about worker's occupations per county is provided in the BA Employment Panel (BAP)[22]. The BAP is a sample of all employees subject to social security in Germany. It contains quarterly information about the occupation, education level, working place among others.

The same prediction can be derived from Berliant *et al.* (2006). Although the authors describe the appearance of knowledge spillovers, the exchange takes place when two workers arrange a meeting. The more similar these workers in their stock of knowledge, the more both sides benefit from their meeting. Resemblance to Coles and Smith (1998) comes from the matching function with IRS that describes the flow of meetings. So again a larger labor market produces more possibilities to meet the 'right' people. With the number of possibilities the selectivity of workers increases, leading to a higher quality of matches and higher productivity in turn. Since in Berliant *et al.* (2006) the distribution of workers is uniform in their knowledge, a rise in city size implies more suitable matches for all types of workers. Again the correlation in occupations between one specific industry and the rest within a county seems closer to the central idea.

Another implementation of a labor pooling measure from Coles and Smith (1998) is to look at the average number of vacancies in each county. In order to get a better grip on the element of suitable worker qualifications, the variable only considers the vacancies for high skilled staff.

3.3.4 Knowledge spillovers

Constructing a measure of knowledge spillovers according to a theoretical model is not trivial. Firstly, because there are few contributions that explicitly model a microeconomic channel, and secondly, because it is challenging to detect spillovers in a dataset. Something that is empirically traceable are job changes. When a worker leaves a firm he takes all his knowledge with him and his new employer might benefit from his experience or from new ideas that this worker brings into the firm. Based on this story Fosfuri and Rønde (2004) provide a theoretical underpinning for the prediction that labor turnover is

[22]The construction is based on the anonymized version of the 3-digit occupational classification of the German Federal Employment Agency, which lists 282 different occupations.

high when agglomeration of firms is driven by knowledge spillovers. One can expect that these knowledge spillovers are less present when the job manual is routine. But the more skilled a worker is the larger the spillover he might bring to the firm. From the BAP I construct a measure of average job changes for each county, considering only those workers who have either a university degree or finished a vocational training.

I employ two more variables to proxy for knowledge spillovers. Since the work of Jaffe *et al.* (1993) patent citations have often been used, because they reveal the flow of new ideas. Patent applications are admittedly less suitable, but are the only data readily available for Germany[23]. I argue that knowledge spillovers are more likely to occur in places with lots of innovative people. It must be taken into account that the possibility to meet and interact with these people diminishes with county size. So the second measure for knowledge spillovers is patent applicants per worker.

The third measure is also an indicator for the innovativeness of a region. The Federal Ministry of Education and Research (BMBF) grants funding to companies, universities, institutions of higher education and R&D for research in areas that the BMBF regards as a force for growth. In other words the BMBF sees these projects as sources for spillovers. The employed proxy is the amount of funding per year and county (in million Euros). Note that despite having the same label 'knowledge spillovers' the mechanism between job changes and the patents / R&D funds variables is distinct. For this reason these proxies are unlikely to be collinear and I will use them simultaneously in regressions. The correlation coefficients between the agglomeration mechanism variables and between the industrial environment variables are shown in tables 11 and 12 in the appendix, respectively.

Concerning endogeneity of these agglomeration variables, I am more confident with the job changes than with the other two spillover measures. It might be the case that the number of patent applicants are correlated with productivity, simply because high productivity firms hire a more innovative personnel than low productivity firms. Similarly high productivity firms might be more successful in acquiring public funds than their competitors. Then these measures would just indicate, where high productivity firms are located, but do not imply the presence of knowledge spillovers. With regard to input linkages and labor market pooling I am carefully optimistic that endogeneity does not

[23]The numbers to construct the patent variable are taken from Greif *et al.* (2006). Unlike all other variables this one solely covers the period from 2000 until 2005 and is therefore the reason why only this period is used in the TFP analysis.

drive the results here. Firstly, because reasoning like above appears implausible in these cases. Secondly, Ellison *et al.* (2010) use a sophisticated set of instruments for similar agglomeration proxies and find their initial OLS results to be fairly stable.

Table 2 presents summary statistics for all the agglomeration variables described above. In addition, table 11 and 12 in the Appendix contains correlation coefficients between the agglomeration mechanisms and between the industrial environment measures, respectively.

Table 2: summary statistics of agglomeration variables

label	proxy	mean	std. dev.
labor market pooling	occupation correlation	0.2304	0.2042
	job vacancies	0.0038	0.0065
knowledge spillovers	job changes	0.0423	0.0079
	public R&D funds	6.7448	12.9999
	patents per worker	0.0012	0.0010
input linkages	input-linkage	1.3293	2.6760
localization	county-ind. employment (E_i^k)	7257.326	16658.45
	county-ind. emp. share (E_i^k/E^k)	0.1253	0.1265
urbanization	$jacobs1$	0.0286	0.0266
	$jacobs2$	0.5828	0.0941
	log employment density	4.6106	1.3708
	log county employment (E_k)	11.1688	0.8646

Notes: The number of observations is 18569 for all variables.

4 Results

4.1 Production functions results

Table 3 reports the results from the estimation of production functions under the four basic specifications. The first column contains the result from a simple OLS regression of equation (1). The coefficients in the second column have been produced, applying only the OP estimation algorithm as described in section 2.1. The third and fourth column result from equation (4), where just the KG procedure has been applied. Finally the fifth and sixth column refer to equation (8) and (12), the preferred specification. In both estimations where unobserved output prices are substituted, adjusted and unadjusted coefficients are reported. In the two cases, where the selection bias has been taken care of, all variables capturing agglomeration mechanisms have been used as predictors for productivity (subsumed in the parameter G_t^k in the above equations). Controls for the share of high skilled workers, a west-dummy and industry fixed effects are included in all production functions.

Table 3: basic production function coefficients

	OLS	OP	KG		OP/KG	
	$\widetilde{\alpha}$	$\widetilde{\alpha}$	$\widetilde{\alpha}$	α	$\widetilde{\alpha}$	α
materials	0.6522	0.6484	0.6512	0.8230	0.6474	0.8049
	(0.0063)	(0.0043)	(0.0063)		(0.0043)	
labor	0.3300	0.3287	0.3312	0.4186	0.3297	0.4100
	(0.0086)	(0.0057)	(0.0087)		(0.0057)	
capital	0.0472	0.0465	0.0472	0.0596	0.0458	0.0569
	(0.0037)	(0.0006)	(0.0035)		(0.0006)	
demand ela.	-	-	5.58		5.84	
			(1.1797)		(1.6137)	
west	0.1212	0.1012	0.1204	0.1522	0.1007	0.1272
	(0.0090)	(0.0090)	(0.0090)		(0.0061)	
high-skilled share	0.1508	0.1465	0.1481	0.1872	0.1434	0.1783
	(0.0178)	(0.0159)	(0.0177)		(0.0161)	
N	18569	18569	18569		18569	
R^2	0.9711	-	0.9711		-	

Notes: Cluster robust standard errors are given in parenthesis. In the OP and OP/KG case the standard errors were obtained by bootstrapping. Coefficients for the industry fixed effects are omitted.

Beginning in column 1, all coefficients have the expected magnitude and are highly significant. Scale elasticities of labor, capital and intermediate inputs sum to 1.03, hence this production function exhibits increasing returns to scale. A simple Wald test confirms that the sum $\widetilde{\alpha}_k + \widetilde{\alpha}_l + \widetilde{\alpha}_m$ is significantly different from unity. The distinction between the first and the second column is, that I have accounted for the positive correlation between inputs and productivity. Just as predicted by theory, we see lower scale elasticities for capital, labor and materials, but still the sum of these coefficients indicate the presence of increasing returns to scale.

In estimating the production function according to Klette and Griliches (1996), I found that the year-industry specific term $(r^s_{It} - p^s_{It})$ did not exhibit enough temporal variation to identify industry specific demand elasticities in the presence of industry fixed effects. For this reason, I opted to keep the industry fixed effects and constrain the demand elasticity to be equal in all industries. In the KG case this elasticity across all industries is estimated to 5.58. Recall that through the combination of production and demand side, the original coefficients are reduced form parameters. After rescaling by $\frac{\sigma}{\sigma-1}$

(in column 4) all scale estimates are higher than in the prior models and the production function exhibits substantial returns to scale.

Combining this KG specification with the OP procedure, again I find lower scale estimates due to the correction of the transmission bias. Here, the demand elasticity is 5.84. I have also estimated the same equation with industry specific demand elasticities and find their range to be quite narrow[24]. The highest demand elasticities are in 'wholesale and retail trade' (6.84), in 'food, beverages and tobacco' (6.54) and in 'transport, storage and communication' (6.43). The industries least sensitive to price differences are 'wood products' (5.41), 'other transport equipment' (5.43) and 'precision and optical instruments' (5.50). The latter industries tend to produce less standardized products than the three industries with the highest demand elasticities, so this finding accords with our intuition.

To wrap up, all estimated parameters are quite plausible. Scale estimates are positive, significant and sum to somewhat more than unity. Also as expected, the west-dummy is highly significant and indicates that establishments in West Germany generate around 12% higher revenues with the same amount of inputs. Considering that demand elasticities are estimated at the firm level, their range from 5.4 to 6.8 seems reasonable, too. These numbers conform to the findings of other studies, e.g. De Loecker (forthcoming). Even the author had segment specific physical output quantities available, he finds demand elasticities for subsectors of the textile industry between 2.8 and 6.2 in a similar setting. Also based on a CES utility function, Hanson (2005) estimates market potential functions from county specific data for the US. He obtains demand elasticities in a range of 5 to 7.5.

4.2 Agglomeration mechanisms results

Table 4 presents results from regressing each of the six proxies for agglomeration mechanisms separately on each of the four basic TFP measures, obtained from the production functions described in the previous subsection. All estimations control for year and industry fixed effects. In addition, all agglomeration variables are standardized to have a zero mean and a standard deviation of one, in order to provide direct comparability of their relative impact. All variables have a positive coefficient and are not very distinct in size across the different TFP measures. Regarding the strength of the proxies, R&D and the occu-

[24]Results are not reported, but are available upon request. The reported results were estimated from an equation without industry fixed effects.

pational structure rank on top in all versions. Differences in the significance level across columns 1-4 emerge only in the patent and input-linkage variables. Before going deeper into interpretations, we want to inspect multivariate regressions, because as argued above, they will provide us with more reliable insights about the relative importance and magnitude of microeconomic agglomeration channels.

Table 4: agglomeration mechanisms in univariate regressions

	OLS	OP	KG	OP/KG
occ-corr	0.0154	0.0190	0.0235	0.0288
	(0.0010)	(0.0013)	(0.0000)	(0.0000)
R^2	0.0024	0.0053	0.0059	0.0086
vacancies	0.0078	0.0101	0.0096	0.0121
	(0.0283)	(0.0258)	(0.0074)	(0.0068)
R^2	0.0016	0.0046	0.0036	0.0065
job-change	0.0116	0.0151	0.0124	0.0158
	(0.0011)	(0.0008)	(0.0005)	(0.0004)
R^2	0.0022	0.0052	0.0041	0.0070
patents	0.0069	0.0087	0.0144	0.0178
	(0.1422)	(0.1437)	(0.0023)	(0.0024)
R^2	0.0015	0.0045	0.0045	0.0074
R&D	0.0151	0.0189	0.0182	0.0224
	(0.0010)	(0.0012)	(0.0001)	(0.0001)
R^2	0.0029	0.0058	0.0055	0.0083
input-linkage	0.0059	0.0080	0.0044	0.0058
	(0.0219)	(0.0156)	(0.0894)	(0.0718)
R^2	0.0013	0.0043	0.0030	0.0059

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

Table 5 contains the results from regressions of the basic TFP measures against all six agglomeration variables. Under the preferred specification (column 4), the labor market pooling measure and two of the knowledge spillovers are still positive and significant. More precisely, the number of job changes and the amount of funds for research projects positively affect the average productivity of firms in a county, though the relative impact of R&D spillovers is slightly higher. However, firms benefit considerably more from a local labor market with an occupational structure similar to their own industry. If the endogeneity bias and the omitted price bias are not accounted for, the magnitude of these positive effects is underestimated. In fact the TFP measure from the OLS regression yields 20-42% lower coefficients. Simple OLS and the KG regressions would even suggest that these three significant mechanisms have the same importance. Furthermore, table 5 reveals that patent applications, input linkages and job vacancies in a county are not major sources of agglomeration externalities, or at least the way these variables are constructed does not capture the underlying mechanism well. This might especially be true for the input linkage proxy, whose construction could have been improved with information about local input-output flows. Concerning the considerable differences in the performance of the patent proxy in multivariate and univariate regressions it might be possible that its significance in the univariate regression is caused by positive correlation with some of the other agglomeration proxies. However, the correlation coefficients among the agglomeration variables displayed in table 11 in the appendix are all below 0.3 and variance inflation factors show, that the multivariate regressions do not suffer from multicollinearity.

Table 5: agglomeration mechanisms in multivariate regressions

	OLS	OP	KG	OP/KG
occ-cor	0.0098	0.0142	0.0115	0.0167
	(0.0440)	(0.0037)	(0.0545)	(0.0047)
vacancies	0.0047	0.0051	0.0059	0.0062
	(0.1501)	(0.1207)	(0.1421)	(0.1163)
job-changes	0.0092	0.0088	0.0116	0.0110
	(0.0093)	(0.0132)	(0.0074)	(0.0106)
patents	-0.0004	0.0038	-0.0004	0.0048
	(0.9396)	(0.4203)	(0.9472)	(0.4009)
R&D	0.0105	0.0108	0.0129	0.0131
	(0.0237)	(0.0208)	(0.0238)	(0.0207)
input-linkage	0.0044	0.0037	0.0057	0.0046
	(0.0921)	(0.1547)	(0.0750)	(0.1460)
R^2	0.0041	0.0064	0.0066	0.0089
F	3.88	4.58	7.99	8.60
N	18569	18569	18569	18569

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

A direct comparison between the OP and the OP/KG is especially insightful. In the OP case, the TFP estimate contains price variation. That is, because unobserved firm level prices have not been accounted for, they are included in the residual term. So instead of regressing true TFP against the agglomeration variables, the estimating equation in fact looks like this

$$\omega_{jt} + p_{jt} = \beta_0 + G_t^k + e_{jt}$$

Under this OP specification, we observe lower coefficients in table 5 for each of the six agglomeration mechanisms subsumed in G_t^k. Hence unobserved firm level prices are negatively correlated with G_t^k. On the one hand, this suggests that firms quote on average lower prices in counties characterized by (1) having a similar occupational structure to their own industry, (2) high public R&D funding and (3) a high labor turnover. Because these characteristics are also associated with higher firm TFP, this finding, on the other hand, is in line with the prediction that high productivity firms quote lower prices (Melitz 2003). The same interpretation holds from a comparison between the results of the OLS and the KG productivity estimate in table 5. Likewise the first TFP measure incorporates price variation while the latter does not.

Another interesting question is, whether these agglomeration mechanisms differ between industries. Due to the demanding data requirements of this investigation, the number of observations is quite low in some of the 22 industries. Therefore, I combined industries according to their R&D intensity into four groups (compare table 1 above). Table 6 contains the results from the regression of those agglomeration proxies, which exhibited a significant coefficient in the multivariate regressions, against the OP/KG productivity.

Table 6: agglomeration mechanisms for industry groups

	OP/KG			
	[1]	[2]	[3]	[4]
occ-cor	0.0218	0.0119	0.0199	0.0183
	(0.0401)	(0.2812)	(0.1991)	(0.0521)
job-changes	0.0147	-0.0005	0.0300	0.0099
	(0.0845)	(0.9540)	(0.0106)	(0.1019)
R&D	0.0178	0.0033	0.0330	0.0154
	(0.0899)	(0.7727)	(0.1973)	(0.0503)
R^2	0.0108	0.0133	0.0205	0.0079
F	2.3955	5.5014	3.7879	5.7806
N	2920	3228	2150	10271

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

High-tech industries (column 1) exhibit a strong positive correlation between TFP and the labor market pooling proxy. The magnitude of this impact is higher than in the pooled industry case. Only at the 10% significance level do job-changes and R&D funding show a positive influence on TFP as well. In medium-tech sectors, no significant influence is found for either of the variables. For low-tech industries a higher labor turnover is associated with a higher productivity level, whereas for non-manufacturing industries a positive impact comes from the occupational correlation and from R&D projects. Altogether it seems that firms from the most R&D intensive sectors and non-manufacturing industries are more prone to agglomeration externalities than establishments from medium and low technology sectors. As a first robustness check I excluded all non-manufacturing industries from the investigation and found all results presented so far to be largely unchanged.

4.3 Industrial environment results

Table 7 displays the results from multivariate regressions using the industrial environment proxies. Across the four basic TFP measures the emerging picture is quite uniform. There is no sign that the industrial diversity is positively correlated with firm level TFP. Recall that for both diversity measures the theory of Jane Jacobs predicted a negative coefficient. In contrast, we see that the share of the three largest industries in a county ($jacobs2$) exerts a *positive* and significant effect on productivity. Alongside, only city size shows significant coefficients in columns 1 to 6[25]. Remarkably, the two significant proxies again grow in magnitude, when the transmission bias and the omitted price bias are accounted for.

These multivariate regression also reveal that the share of the three largest industries dominates the effect of the share and size in firm's own industry. In univariate regressions each of these three proxies shows a significant influence on the OP or OP/KG TFP measure. In column 6 of table 7 the dominant variable $jacobs2$ was excluded, leading to a much higher and more significant coefficient of the own industry employment share. These tests in columns 5 and 6 underline the robustness of the results, because they leave the previous conclusions unchanged: (1) doubling the size of a county is associated with a 2% to 3% higher firm level productivity. (2) The industrial specialization, either captured through the employment share of the own industry or the three largest industries in a county has a positive influence, whereas no significant effect is found for industrial diversity.

[25]The density of a county is not included in these regressions, because it is highly correlated with city size. However, when I replaced city size with the density variable, qualitatively similar results were obtained.

Table 7: TFP against urbanization and localization variables

	OLS	OP	KG	OP/KG	OP/KG	OP/KG
E^k	0.0124	0.0158	0.0149	0.0189	0.0175	0.0288
	(0.0409)	(0.0092)	(0.0439)	(0.0098)	(0.0139)	(0.0000)
E_i^k	0.0029	0.0030	0.0042	0.0042	0.0044	0.0018
	(0.6371)	(0.6305)	(0.5826)	(0.5763)	(0.5566)	(0.8137)
E_i^k/E^k	-0.0049	0.0010	-0.0084	-0.0003	0.0002	0.0177
	(0.5749)	(0.9133)	(0.4297)	(0.9755)	(0.9867)	(0.0763)
$jacobs2$	0.0213	0.0230	0.0262	0.0279	0.0293	-
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
$jacobs1$	0.0027	0.0034	0.0035	0.0043	-	-
	(0.5732)	(0.4848)	(0.5566)	(0.4670)		
R^2	0.0064	0.0093	0.0089	0.0118	0.0117	0.0081
F	5.62	6.98	10.15	11.45	12.72	10.52
N	18569	18569	18569	18569	18569	18569

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

5 Robustness checks

In this section I discuss results from four different specifications of the original OP framework: (1) the Levinsohn and Petrin (2003) estimation approach, which relies on a different control function than Olley and Pakes (1996), (2) the Ackerberg *et al.* (2006) correction for the OP procedure, (3) taking value added instead of revenue based production functions, (4) using labor productivity instead of estimated TFP to identify agglomeration economies;

5.1 Levinsohn and Petrin (2003) estimation

Levinsohn and Petrin (2003) (LP, henceforth) use intermediate input demand $m_{jt} = m_t'(k_{jt}, \omega_{jt})$ instead of investment demand to control for unobserved productivity. Their modification is suitable for datasets in which a large number of firms report missing or zero investments. In the present case the sample size would only be slightly increased, because the construction of the capital variable already relies on firms' investments[26]. However, testing the LP estimation provides two other robustness checks. Firstly, before we assumed that productivity is the only unobserved factor in the investment demand and that the function is monotonic in productivity. Obviously, in the LP framework we have to make these two assumptions with respect to the intermediate inputs

[26]For better comparability of results I condition the LP estimation on the same sample as the other estimations before.

demand m_{jt} [27]. Yet, observing considerable different results from both models would lead to the conclusion, that one of control functions is defective. Secondly, in contrast to the prior OP estimation the scale elasticity $\widetilde{\alpha}_m$ is only identified in the second stage. If the identification of perfectly variable inputs, such as m_{jt}, would be in error, we should see considerable different estimates for α_m. To be more precise, the first and second stage estimation for the LP estimation are

$$\widetilde{r}_{jt} = \widetilde{\beta}_0 + \widetilde{\alpha}_l l_{jt} + \frac{1}{\sigma}(r^s_{It} - p^s_{It}) + \phi'_t(k_{jt}, m_{jt}, G^k_t) + \zeta z_{jt} + u_{jt}$$

$$\frac{1}{T}\frac{1}{N}\sum_t \sum_j \hat{\xi}_{jt}(\widetilde{\alpha}_k, \widetilde{\alpha}_m) \cdot \begin{pmatrix} k_{jt} \\ k_{jt-1} \\ m_{jt-1} \end{pmatrix}$$

Regarding the second stage estimation, recall that the innovation shock ξ_{jt} to productivity evolves *during* t and $t-1$ and therefore will partly be correlated with the choice of M at t. Therefore the identification of $\widetilde{\alpha}_m$ is based on moment conditions of lagged intermediate inputs. Note, that I also include lagged capital as an additional moment, because it increases the efficiency substantially. Here, an estimate for the innovation shock ξ_{jt} is residually computed from non-parametric regression of $\omega_{jt}(\widetilde{\alpha}_k, \widetilde{\alpha}_m)$ on $\omega_{jt-1}(\widetilde{\alpha}_k, \widetilde{\alpha}_m)$ [28]. In doing so, I use $\omega_{jt}(\widetilde{\alpha}_k, \widetilde{\alpha}_m) = \hat{\phi}'_t - \widetilde{\alpha}_k k_{jt} - \widetilde{\alpha}_m m_{jt}$ from the first stage.

5.2 Ackerberg *et al.* (2006) estimation

The Olley and Pakes (1996) and the Levinsohn and Petrin (2003) approach have been criticized by Ackerberg *et al.* (2006) (henceforth ACF) because of their assumptions on the variable inputs. The authors consider that L and M are not chosen independently, but rather might be functions in k_{jt} and ω_{jt},

[27] The lower panel of figure 1 in the appendix shows a graphical assessment of this assumption. The surface in the LP/KG case is increasing much sharper in productivity but also decreasing earlier and faster. This suggests that the required invertability condition is more likely to hold for the investment demand control function.

[28] Here and in the following ACF/OP/KG estimation the adjustment for the selection bias is omitted for the following reasons. Firstly, the empirical importance of the selection bias in this dataset is low. This finding has already be made in the studies of Olley and Pakes (1996) and Levinsohn and Petrin (2003). Secondly, the survival probability under the ACF correction would be dependent on all three lagged inputs, lagged agglomeration variables *and* l_{jt} and m_{jt}, due to the dynamic consequences of L and M. Hence the sample size is reduced by one period, perturbating the comparisons with the results from the other estimation procedures.

just like firm's investments are. Substituting by $\omega_{jt} = h_t(k_{jt}, i_{jt}, G_t^k)$ yields

$$l_{jt} = l_t(\omega_{jt}, k_{jt}) = l'_t(k_{jt}, i_{jt}, G_t^k) \qquad \text{and} \tag{13}$$

$$m_{jt} = m_t(\omega_{jt}, k_{jt}) = m'_t(k_{jt}, i_{jt}, G_t^k) \tag{14}$$

Plugging these functions into the production function (8), reveals that both equation (13) and (14) are perfectly collinear with the term $\phi_t(k_{jt}, i_{jt}, G_t^k)$, thus preventing the identification of α_l and α_m in the first stage. ACF propose a modified estimation algorithm, which relies on a different timing assumption of input choices. Labor and materials are now decided in $t-b$, where $b \in [0, 1]$. That is, they are neither variable inputs nor as deterministic as the choice of capital. The crucial implication is, that thereby labor and materials become state variables and hence are part of the firm's dynamic optimization problem. Now, the investment demand (still chosen in t) is $i_{jt} = i'_t(k_{jt}, l_{jt}, m_{jt}, \omega_{jt}(G_t^k))$. Proceeding as in the OP case gives the following first stage production function, where neither scale elasticity is identified.

$$\widetilde{r}_{jt} = \widetilde{\beta}_0 + \frac{1}{\sigma}(r_{It}^s - p_{It}^s) + \phi'_t(k_{jt}, l_{jt}, m_{jt}, i_{jt}, G_t^k) + \zeta z_{jt} + u_{jt} \tag{15}$$

Still, this stage is necessary to identify estimates for ϕ'_t, σ and ζ. Even under the new timing assumptions, ξ_{jt} will partly be correlated with the input choice of L and M at $t-b$. Nonetheless the following moment conditions hold

$$E\left[\xi_{jt} \cdot \begin{pmatrix} k_{jt} \\ k_{jt-1} \\ l_{jt-1} \\ m_{jt-1} \end{pmatrix}\right] = 0 \tag{16}$$

Apart from the new $\omega_{jt}(\alpha_k, \alpha_l, \alpha_m) = \hat{\phi}'_t - \alpha_k k_{jt} - \alpha_l l_{jt} - \alpha_m m_{jt}$, the remainder of the procedure is as described in the LP case before.

5.3 Value added production functions and labor productivity

Taking value added (VA) instead of revenue production functions can be seen as another response to the critique in Ackerberg *et al.* (2006). Of course, value added production functions sidestep part of the problem problem, because the perfectly variable input M does not have to be identified at all. Instead of changing the assumptions on the timing of input choices, according to Bond and Söderbom (2005) identification of perfectly variable inputs can be achieved, if the input factor encounters adjustment costs. That is a maintainable assumption in the case of labor. Thus, either of the OP, LP or KG estimation algorithms can be performed analogous to the revenue case. Due to space constraints just the simple OP adjustment is presented. Nevertheless, this does not imply that value added is the superior measurement of production, cf. the discussion in Basu and Fernald (1997). At last, the following tables also contain regressions with log labor productivity as dependent variable, being computed as log revenues minus log labor input. The purpose of this exercise is to ascertain, whether a measure, which is not estimated from a production function, leads to the same inference as TFP measures.

5.4 Results for the additional TFP measures

Coefficients from the estimation of the additional production functions are given in table 8. Under the ACF correction in columns 1 and 2 the labor coefficient is almost unchanged in comparison to the OP/KG model. However, the capital coefficient is reduced by more than 50%, casting doubt on the accuracy of the procedure. This finding is unexpected, because the capital coefficient has already been identified in the second stage in the prior OP estimations. The LP/KG procedure results in columns 3 and 4, where the materials coefficient is also identified in the second stage, are much closer to the OP/KG estimation. The demand elasticity and the control variables remain quite stable in both extensions. Finally, the last column shows the results from the value added production function for completeness.

Of more importance is the question, if these productivity estimates lead to different conclusions regarding agglomeration economies? The following tables 9 and 10 display results from multivariate regressions with one of the four additional TFP measures as the dependent variable and agglomeration mechanisms and industrial environment proxies, respectively, as covariates. Table 9 confirms that occupational correlation exerts the highest influence on whichever TFP measure. For the ACF, VA and LP productivity measures job changes and R&D funding also show a positive and significant coefficient. The *relative* size of their impacts is roughly equal to the OP/KG case before. In fact, results from the LP productivity are in all respects very similar to the preferred estimation. Column 3 reminds us that results from revenue and value added production functions are not comparable quantitatively. The value added TFP would imply that a one standard deviation increase in public R&D expenditure for innovative projects would lead to a productivity increase of 2.2%, whereas

Table 8: additional production function coefficients

	ACF/OP/KG		LP/KG		VA/OP
	$\widetilde{\alpha}$	α	$\widetilde{\alpha}$	α	$\widetilde{\alpha}$
materials	0.6131	0.7623	0.6337	0.7879	-
	(0.0045)		(0.0046)		
labor	0.3282	0.4080	0.3351	0.4166	0.9271
	(0.0399)		(0.0059)		(0.0089)
capital	0.0206	0.0256	0.0378	0.0470	0.1308
	(0.0056)		(0.0058)		(0.0014)
demand ela.	6.29		5.99		-
	(1.8115)		(1.7256)		
west	0.1078	0.1340	0.1015	0.1262	0.2549
	(0.0059)		(0.0058)		(0.0159)
high-skilled share	0.1479	0.1839	0.1363	0.1695	0.4688
	(0.0166)		(0.0160)		(0.0334)
N	18569		18569		18569

Notes: Bootstrapped standard errors are given in parenthesis. Industry fixed effects are included in all models.

Table 9: additional productivity measures against agglomeration mechanism proxies

	ACF/OP/KG	LP/KG	VA/KG	L-prod
occ-cor	0.0304	0.0209	0.0588	0.0883
	(0.0000)	(0.0004)	(0.0000)	(0.0000)
vacancies	0.0051	0.0060	0.0115	0.0141
	(0.2151)	(0.1291)	(0.1113)	(0.0275)
job-changes	0.0096	0.0106	0.0216	0.0117
	(0.0341)	(0.0136)	(0.0089)	(0.1319)
patents	0.0176	0.0084	0.0179	0.0422
	(0.0033)	(0.1446)	(0.1012)	(0.0000)
R&D	0.0154	0.0139	0.0227	0.0225
	(0.0105)	(0.0151)	(0.0416)	(0.0432)
input-linkage	-0.0093	0.0006	0.0000	-0.0231
	(0.0112)	(0.8518)	(0.9953)	(0.0052)
R^2	0.0416	0.0148	0.0116	0.2315
F	10.85	8.72	6.32	15.37
N	18569	18569	18569	18569

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

inference from a revenue based productivity measure would only imply a 1.4% increase. Apart from the quantitative divergence the main conclusions from the OP/KG model remain valid. However, somewhat more differences appear using labor productivity or the ACF TFP. The latter model's estimates in the first column suggest that the number of patents have a comparable positive impact to the public R&D funding. Surprisingly, input linkages show a negative coefficient, but as argued above, its construction is not optimal. In contrast to all TFP estimates, agglomeration proxies are able to explain a large part (23%) of the variation embodied in labor porductivity. That is, the agglomeration proxies catch up variation in labor productivity that firm specific differences would have explained. As a consequence, except for job changes, the labor productivity measure lends support to all agglomeration channels.

Finally table 10 displays the results from multivariate regressions employing the urbanization and localization proxies. County size and the share of the three largest sectors in a county have a highly significant and positive coefficient in all four models. The findings from the LP productivity are again almost identical to those from the OP/KG measure in column 4 of table 7. Surprisingly, taking the ACF productivity as the dependent variable results in a large and highly significant coefficient for the own industry employment share, indicating that an increase in the local share of an industry by 12% makes firms in that industry about 6% more productive. Apart from this, the magnitude of county size and the three largest industries' share in a county are comparable to the LP and OP/KG model. The finding, that both specialization proxies exert a positive impact at the same time, is confirmed by VA TFP and labor productivity. Yet, the remarkably high significance level of all covariates and the high R^2 point out, that labor productivity embodies additional variation other than true productivity.

The bottom line I draw from these extensions regarding both the agglomeration mechanisms and the industrial environment variables, is that: (1) the results from the preferred OP/KG TFP measure are definitively reinforced. (2) There is some significant indication for all agglomeration proxies, even those that have not been significant in the OP/KG case, but these findings do not appear stable. (3) Industrial diversity of a region is not associated with higher TFP in *any* of the regressions. (4) Labor productivity is a imprecise measure and will thus overestimate the agglomeration effects. (5) Productivity estimates from value added function are also likely to produce inflated coefficients. (6) The performance of the LP estimation method is very close to

Table 10: additional productivity measures against urbanization and localization variables

	ACF/OP/KG	LP/KG	VA/OP	L-prod
E^k	0.0255	0.0209	0.0573	0.0507
	(0.0009)	(0.0043)	(0.0001)	(0.0004)
E_i^k	0.0070	0.0053	0.0084	0.0382
	(0.3969)	(0.4957)	(0.5984)	(0.0202)
(E_i^k/E^k)	0.0609	0.0173	0.0479	0.1431
	(0.0000)	(0.1038)	(0.0250)	(0.0000)
$jacobs2$	0.0251	0.0271	0.0482	0.0320
	(0.0000)	(0.0000)	(0.0000)	(0.0029)
$jacobs1$	0.0079	0.0052	0.0050	0.0122
	(0.1985)	(0.3743)	(0.5421)	(0.1757)
R^2	0.0474	0.0182	0.0145	0.2357
F	16.45	12.18	8.87	18.41
N	18569	18569	18569	18569

Notes: p-values in parentheses are computed by the use of cluster-robust standard errors. A constant, year and industry fixed effects are included in all estimations.

the OP procedure both regarding the scale estimates and the inference on the agglomeration mechanisms, if the identical sample is used.

6 Concluding comments

The present investigation demonstrates that in order to obtain a reliable productivity measure, it is important to account for unobserved output prices and the endogeneity of input choices in the production function. Based on such a TFP measure, the proxies for agglomeration economies are found to have coefficients of higher magnitude and significance. The main contribution of the paper is to examine the relative strength of microeconomic agglomeration channels on firm's productivity. Examined separately, each of the six different agglomeration variables shows some significant indication, whereas only three of them were still significant in multivariate estimations. The most important impact on firms' productivity was found to be transmitted via the labor market. Like predicted by matching models, firms in industries that have a similar occupational structure to the remainder firms in that county were on average more productive, due to more opportunities in finding suitable workers. Besides, the data revealed that public R&D funding to innovative projects exerted a positive productivity spillover to establishments in their vicinity. Another source of knowledge spillovers was found to operate through job changes of qualified workers, whereas input relations exerted no significant effect.

Concerning the industrial environment, the underlying data confirms that firms are on average more productive in large counties. A doubling of employment in a county entails a 2-3% higher firm TFP. Moreover, the study supports the hypothesis that a specialized county structure is beneficial to firms, whereas no evidence is found for Jacobs economies. Both results on agglomeration mechanisms and the industrial environment under the preferred specification are qualitatively robust to the use of different TFP estimates yet differences emerge regarding the size and significance level of the proxies. Especially estimates from value added productions functions and labor productivity are likely to result in inflated coefficients.

By no means is this investigation exhaustive in the way agglomeration economies might be transmitted to firms. Different and more refined proxies can surely be constructed in richer datasets. Paying more attention to sector characteristics is also likely to disclose more about the nature of agglomeration economies.

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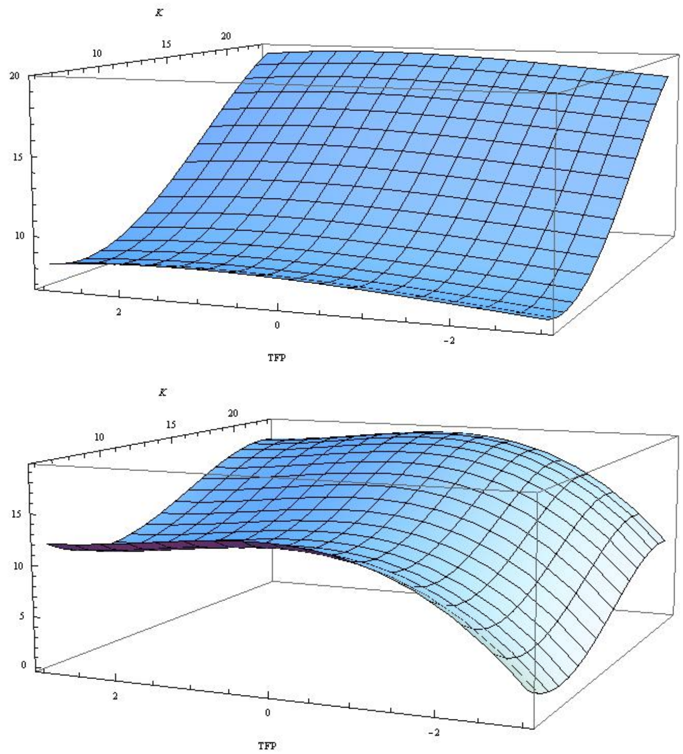
appendix

Figure 1: visualization of the invertability condition



Notes: The upper graph results from regression firm's log investments against a third order polynomial in log capital stock and log OP/KG productivity. The lower figure was constructed by regressing firm's log intermediate inputs against a third order polynomial in log capital stock and log LP/KG productivity.

Table 11: correlation coefficients of agglomeration mechanism variables

	E^k	occ-corr	vacancies	job-changes	patents	R&D	input-link.
E^k	1						
occ-corr	0.4573	1					
vacancies	0.2176	0.1187	1				
job-changes	0.1158	0.0871	0.0547	1			
patents	0.1909	0.2389	0.1287	0.1361	1		
R&D	0.7191	0.2677	0.1917	0.2496	0.2430	1	
input-link.	0.1069	-0.0605	0.0151	0.0024	-0.0115	0.0626	1

Table 12: correlation coefficients of industrial environment variables

	E_i^k	E_i^k/E^k	$jacobs1$	$jacobs2$	density	E^k
E_i^k	1					
E_i^k/E^k	0.5211	1				
$jacobs1$	-0.0329	0.0691	1			
$jacobs2$	0.2527	0.2859	0.2575	1		
density	0.3959	0.1838	0.0171	0.5762	1	
E^k	0.5506	0.1067	-0.1492	0.3240	0.7144	1