Agglomeration Effects in Ethiopian Manufacturing*

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Abstract

This paper investigates whether there are agglomeration effects in Ethiopia's manufacturing sector, using a rich panel census firm-level dataset for 1996-2004. The empirical evidence indicates that the geographical agglomeration of own-sector firms impacts positively on firm-level productivity. The evidence also indicates that such productivity gains feeds into higher short-term growth rates of employment, and hence, in the long term, larger firms.

Keywords: Agglomeration economies, African manufacturing, Ethiopia, productivity, firm growth.

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1. Introduction

Starting with Marshall (1920), many economists have argued that geographical agglomeration, or clustering, of enterprises can be a source of improved firm performance.[1] The basic idea is that, by locating close to suppliers, customers and competitors, an enterprise may be able to benefit from information spillovers, obtain better access to (skilled) labor, face lower transaction costs, etc. Henderson (1997) provides empirical evidence indicating that agglomeration economies have been an important source of employment growth in five U.S. manufacturing industries between 1977 and 1990. For less developed economies, little quantitative evidence on these mechanisms exists however, and for Sub-Saharan Africa – as far as we know - there is none.[2] In this paper we use census panel data on Ethiopian manufacturing firms to empirically analyze the effects of enterprise clustering on two key aspects of firm performance: productivity and firm growth.

Enterprises in Ethiopia, and most other countries in Sub-Saharan Africa, typically operate in thin local markets, producing mostly products with low value added. This, of course, stands in sharp contrast to developed countries, where markets are relatively well integrated, competitive and technologically advanced. Whether agglomeration economies are important in fragmented, uncompetitive and technologically underdeveloped markets is an open - and empirical - question. What seems almost certain is that agglomeration economies in Africa are rather different to those in developed economies. For example, it would seem unlikely that technological spillovers are as significant a source of agglomeration effects in Ethiopia as in Silicon Valley. Other sources of agglomeration economies may be very important, however. Kingdon, Sandefur and Teal (2007) observe that large labor cost differentials exist across firms and sectors in Africa, indicating that labor markets are uncompetitive. Enterprise clustering may result in a thicker labor market, improving access to labor

[1] Sonobe and Otsuka (2006, p.4) define a cluster as "an industrial cluster as the geographical concentration or localization of enterprises producing similar or closely related goods in a small area". Porter (1990, p. 18) defines it as a "geographical concentration of interconnected companies and institutions in a particular field" Swann et al (1998, p 1) define it as "a large group of firms in related industries at a particular location". Schmitz and Nadvi (1999) simply define industrial cluster as "sectoral and spatial concentration of firms."

[2] The closest we have found to our application is the analysis in Fafchamps and El Hamine (2004), and Fafchamps (2004). These studies analyze agglomeration economies in Moroccan manufacturing. Morocco, of course, is rather much more developed than most countries in Sub-Saharan Africa.

and lowering search costs. Collier and Venables (2007) argue that spatial concentration of infrastructure and other investment climate services may be cost-effective ways of lowering the transaction costs faced by African firms. McCormick (1999) argues that geographical proximity is important for business relationships that are, in the absence of efficient contract enforcement and strong institutions, largely built on trust and informal connections.

The objective of this paper is thus to analyze whether agglomeration effects are economically important in Ethiopia, an economy where productivity gains in the non-farm sector are urgently needed. Our data are well suited for this purpose. Access to census data implies that we can define agglomeration variables based on complete data on all members of the relevant economic cluster. We are therefore able to measure agglomeration variables more accurately than would be possible with survey datasets. The panel dimension in the data enables us to allow for time invariant unobserved heterogeneity in performance across firms. This is important, given that cluster characteristics and firm performance may be correlated for many reasons, some of which may have nothing to do with agglomeration per se. The wide geographical coverage in the data is another unusual feature compared to other African firm-level datasets, and ensures there is plenty of variation in the cluster variables across firms. As our main goal is to investigate the effects of agglomeration in clusters on performance, this is clearly of vital importance. Finally, the relatively broad coverage of industrial sub-sectors in the data enables us to investigate whether agglomeration effects are sector-specific or not. The findings will tell us whether sectoral composition matters for the performance of clusters.

The remainder of the paper is organized as follows. In the next section we develop our conceptual framework building on the literature on agglomeration economies. In section 3 we present the data and define the variables to be used in the analysis. The results are presented in Section 4, while Section 5 concludes with a summary of our results and policy conclusions.

2. Conceptual Framework

In the first part of this section we provide a brief background to the literature on agglomeration effects on firm performance. In the second part of the section, we outline our own empirical framework.

2.1 Agglomeration and industrial development

In a classical reference on agglomeration economies, Marshall (1920) argued that the agglomeration of firms in similar or related activities lead to a number of localized external economies, such as improved access to a pool of specialized workers, quick access to suppliers of inputs and better access to knowledge relevant for the firm. The modern literature emphasizes the latter mechanism, i.e. information spillovers, as perhaps the main agglomeration mechanism. Firms located close to each other are well placed to learn from each other about new technologies, new ways of marketing, or new management techniques, for example. Such externalities can clearly enhance the technological capacity of firms. In countries with weak formal institutions, informal contract enforcement and cooperation are important for business, and likely work better if the parties involved are located close to each other (McCormick, 1999). Physical proximity could also make firms better informed about which entrepreneurs can be trusted.

Apart from information externalities there is a wide range of agglomeration mechanisms that lower the operating costs of the firms. The cost of labor may fall as a result of agglomeration, since locating in a large local labor market makes it easier to find specialized labor (this is sometimes referred to as the thick labor market externality; Glaeser et al, 1992). A large local labor market also implies scope for specialization and division of labor among enterprises. The cost of fixed capital may be lower in locations where there is a functioning market for second hand capital (e.g. equipment) so that firms' investment decisions are reversible rather than irreversible (Dixit and Pindyck, 1994). Proximity to input suppliers and consumers and shared infrastructure lowers transportation and transaction costs. Joint location may also facilitate sharing of indivisible goods and facilities. Clusters may also attract traders that make it easier for firms to market their goods.

A somewhat distinct effect of enterprise agglomeration on performance is through competition. The influx for firms into a geographical cluster may lead to some or all of the agglomeration effects discussed above, but it also plausibly increases the degree of local competition. There has been a lively discussion in the literature about the effect of the degree of concentration of firms on enterprise performance. On the one hand we have the so called MAR hypothesis – after Marshall, Arrow, and Roemer – which says that monopoly helps productivity. The argument is that Schumpeterian entrepreneurs can reap benefits of innovation. The counter-hypothesis is due to Porter and others, who argue that competition has a favorable effect on productivity as firms fight with each other to survive (Porter, 1990). Empirical results are quite mixed. For example, Nickell (1996) finds that competition raises firm-level productivity growth in the UK manufacturing sector, while Combes (2000) finds that competition and total local employment have a negative effect on firm growth in France.

Finally, several authors have argued that agglomeration effects will depend on the sectoral composition of the cluster. Jacobs (1969) argues cross-sectoral effects are important, and that sectoral diversity raises productivity via the exchange of information and pecuniary externalities across sectors. Rosenthal and Strange (2003, p. 12) conclude from their literature review that "doubling city size seems to increase productivity by an amount that ranges from roughly 3-8%", suggesting that agglomeration effects are not sector-specific. Henderson et al. (1995) find that diversity encourages growth in high-tech industries in the U.S. However, Henderson (1997; 2003) and Desmot and Fafchamps (2005) find that, in the U.S., own-sector externalities are much stronger than those generated by other sectors. On balance, the results in the empirical literature seem to indicate that spillovers from own-sector firms have the strongest effects on performance (e.g. Henderson, 2003).

Agglomeration may thus impact on performance through productivity, prices or costs. Fafchamps (2004) argues that the precise channels through which clustering affects performance have never been tested formally, and sets out to do so using firm level data for Morocco.[3] A key result in Fafchamps (2004) is that agglomeration variables affect employment growth, but not via productivity or wages. Fafchamps (2004, p. 27) concludes that "agglomeration variables do not have on firm-level productivity the same effect that they have on aggregate growth, and they do not influence manufacturing growth via their presumed effect on productivity. Yet agglomeration variables have a strong and robust effect on growth." Based on the results, Fafchamps disputes the notion, common in the literature, that agglomeration affects growth through higher productivity.

2.2 Empirical Approach

Our empirical analysis focuses on the effects of agglomeration on productivity and enterprise growth.

Agglomeration effects on productivity

To derive an equation suitable for analysis of the effects on productivity, we start from a three-factor Cobb-Douglas production function as follows:

$$y_{it} = \beta_l \cdot l_{it} + \beta_k \cdot k_{it} + \beta_m \cdot m_{it} + a_{it} + \varepsilon_{it},$$

where y_{it} is log of output, l_{it} denotes log labor, k_{it} is log physical capital, m_{it} is log raw materials, a_{it} is productivity, ε_{it} is a measurement error in output, i,t are subscripts for firm and time, respectively, and β_l, β_k, β_m are parameters. We assume that the productivity term a_{it} contains a component that is observed to managers but unobserved by the econometrician. Hence the factor inputs, which are choice variables, and endogenous. This raises important identification issues.[4] We assume that raw

[3] Fafchamps (2004) looks at the impact of agglomeration on employment, output, investment, and number of firms, and he tests four agglomeration variables, namely total employment in the location, total number of sectors, diversity, and competition.

[4] Estimation of production functions based on micro data has a long and difficult history in economics. A much highlighted problem is that the factor inputs (capital, labor and materials) may be influenced by unobserved factors that also impacts productivity, in which case ordinary least squares or the within estimator will not yield consistent parameter estimates. This has been a common worry in the academic literature for a long time (see Marschak and Andrews, 1944). Sometimes instrumental variables can be used to correct for this type of problem. Blundell and Bond (2000) use such an approach, but offer no theoretical justification for the use of lagged inputs as instruments. The theoretical underpinnings of the estimator proposed by Olley and Pakes (1996) are more explicit, but, as discussed by Ackerberg, Caves and Frazer (2006), this estimator requires strong assumptions to work. Analyzing a structural dynamic model with forward looking firms, Bond and Söderbom (2005) observe that the presence of capital and labor adjustment costs can provide theoretical justification for

material is a flexible input, which given the Cobb-Douglas functional form implies that the optimal level of materials is proportional to the ratio of output to the unit price of raw material. Therefore, given that raw materials is endogenous and that we control for firm fixed effects and sector-specific time trends in the regressions, identification of β_m will not be possible unless i) changes in raw material prices vary across firms within sectors; ii) these changes themselves are predictable by means of instruments; and iii) these instruments at the same are uncorrelated with changes in productivity a_{it}. We are not confident such instruments exist in our data.[5] Therefore, and since the coefficient β_m is not of central importance to our analysis anyway, we "optimize out" raw materials using the first order condition referred to above. With this approach we can re-write the output equation as

$$y_{it} = \alpha_l \cdot l_{it} + \alpha_k \cdot k_{it} + \tilde{a}_{it} + \tilde{\varepsilon}_{it}, \qquad [1]$$

where $\alpha_l, \alpha_k, \tilde{a}_{it}, \tilde{\varepsilon}_{it}$ are equal to $(1-\beta_m)^{-1}$ multiplied by $\beta_l, \beta_k, a_{it}, \varepsilon_{it}$, respectively. It is straightforward to show that this specification applies for log value-added as well (abstracting from a shift in the intercept). The empirical section will contain regression results based on this model, for output as well as for value-added.

We further assume that capital and labor are "quasi-fixed" inputs in the sense that they cannot be freely adjusted without cost in response to shocks to demand, productivity, or costs. Firms will smooth out adjustments over time in order to reduce adjustment costs, so capital and labor will be serially correlated. Lagged values of inputs may therefore be informative instruments. We recognize that the unobserved component of productivity also may be serially correlated, in which case it may be necessary to use deep lags of capital and labor as instruments. For example, if the unobserved component of productivity follows a moving average process of order 1 (MA (1)), while capital and labor are MA(2), then capital and labor dated t-2 will be valid instruments. Whether the time series properties in the data are such that identification can be achieved using this approach is an empirical question, to which we return below.

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using lags as instruments, since capital and labor will be serially correlated in such a case. These authors also note that identification of coefficients on flexible inputs will be difficult in cross-section datasets.

[5] The price of raw materials is unobserved in the data.

Now consider the agglomeration effects on productivity. In general, we write productivity as a function of cluster characteristics whilst allowing for firm fixed effects, sector specific time trends, and a time varying productivity shock:

$$\tilde{a}_{it} = \mathbf{x}_{jt}\mathbf{b} + \mu_i + \theta_{st} + u_{it}$$

where $\mathbf{x}_{jt}$ is a vector of cluster variables, μ_i is a firm fixed effect, θ_{st} is a sector-specific time effect, u_{it} is the dimension of time varying productivity observed to the firms but not to the econometrician, and *j,s* denote cluster and industrial subsector, respectively.[6] In the previous subs-section we discussed various sources of agglomeration externalities. These can broadly be grouped into information externalities, factor cost externalities, competition effects, and sectoral composition effects. The second of these will plausibly affect input decisions, but not productivity. The remaining three may all impact on productivity.

In the empirical literature various ways of defining agglomeration variables can be found. A common proxy for knowledge spillovers is the number of firms in the location (e.g. Henderson, 2003, Fafchamps and El Hamine, 2004, Fafchamps, 2004). The basic idea behind using this variable is that the larger the firm's cluster, the more likely is it that the firm will benefit from agglomeration effects. Henderson (2003) argues that this is a good proxy for knowledge spillovers, preferable to total employment in the cluster. He argues that it is reasonable to suppose that each firm in a cluster experiments with the choice of suppliers, inputs etc. The firm learns from such decisions. Under the hypothesis that knowledge spills over onto other firms in the cluster, it is therefore natural to model total learning in the cluster as proportional to the number of firms, not employment. In the empirical analysis we will consider both definitions. We also distinguish between intra and inter-industry effects

[6] It is important to control for unobserved factors. While a statistically significant relationship between an agglomeration variable and productivity would be consistent with the presence of agglomeration effects, one will not be able say with certainty that such a relationship is indeed driven by agglomeration mechanisms unless all relevant variables driving both productivity and agglomeration are properly controlled for. With cross-section data, distinguishing between true and spurious agglomeration effects is extremely difficult. Panel data enable us to control for unobserved time invariant differences in productivity levels across firms and locations, which is an important advantage.

in this context. We use as our main cluster definition according to which only own-sector firms in the location are part of the cluster, but also consider an alternative one according to which all manufacturing firms in the location that are *not* in the own sector are included.

To investigate whether technological spillovers (somewhat distinct from knowledge spillovers) are important, we construct a proxy for how technologically advanced a cluster is by calculating the proportion of firms in the cluster that have invested in fixed capital (e.g. plant and equipment) over the last year.[7] Furthermore, we construct two variables capturing potentially important dimensions of the market structure within clusters. To capture the extent of economic diversification in the location, we construct a specialty index (opposite of diversity) measuring if a location is specialized in few sectors. This is defined as the deviation from national average of sectoral employment share in the location. To proxy for the level of competition in the cluster we compute the Herfindahl index of sales concentration within industries and clusters.[8] Finally, we construct a dummy variable equal to one for clusters that consist of only one firm, and zero if there are at least two firms in the cluster. The exact definitions of the cluster variables are provided in Table 2.

Taking all of the above into account, our empirical specification of the baseline production function is as follows:

$$y_{it} = \alpha_l \cdot l_{it} + \alpha_k \cdot k_{it} + \mathbf{x}_{jt}\mathbf{b} + \mu_i + \theta_{st} + u_{it} + \tilde{\varepsilon}_{it},$$

The value-added specification is the same, except of course the dependent variable is different. We remove firm fixed effects by taking first differences:

$$\Delta y_{it} = \alpha_l \cdot \Delta l_{it} + \alpha_k \cdot \Delta k_{it} + \Delta \mathbf{x}_{jt}\mathbf{b} + \theta_s + \Delta u_{it} + \Delta \tilde{\varepsilon}_{it}. \qquad [2]$$

We treat capital and labor as econometrically endogenous, assuming these to be correlated with unobserved productivity, u_{it}. This rules out estimating [2] using OLS. Instead, we use instrumental variables in a generalized method of moments (GMM) framework along the lines proposed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991). The cluster variables are initially

[7] The firm's own investment is omitted in these calculations.
[8] The firm's own sales is omitted in these calculations.

assumed predetermined, i.e. $\mathbf{x}_{jt}$ is assumed uncorrelated with u_{it} but may be correlated with lagged values of the residual. We think this is a reasonable starting point in the empirical analysis: firm-level shocks to productivity may impact on cluster variables but this mechanism plausibly operates with a time lag. In the empirical analysis we investigate if the results are robust to treating the cluster variables as endogenous, admitting contemporaneous correlation between cluster characteristics and firm-level unobserved productivity.

Agglomeration effects on (short-term) firm growth

As noted by Fafchamps (2004), agglomeration variables may impact differently on productivity and firm growth. To improve our understanding of the role of agglomeration for enterprise growth, we consider a dynamic labor equation of the following kind:

$$l_{it} = \rho \cdot l_{i,t-1} + \gamma_a \cdot \tilde{a}_{it} + \gamma_k \cdot k_{it} + \gamma_{lk} \cdot k_{i,t-1} - \gamma_w \cdot w_{it} + \psi_i + \varpi_{st} + e_{it},$$

where w_{it} is the wage rate, ψ_i is a firm fixed effect, ϖ_{st} is a sector-specific time effect, e_{it} is a time varying residual, and $\rho, \gamma_a, \gamma_k, \gamma_{lk}, \gamma_w$ are parameters. This specification can be interpreted as a log linear approximation of the structural labor demand equation based on a dynamic model with labor adjustment costs, and in which wages and productivity are the fundamental driving factors. In the empirical section we first establish whether the above specification gives results that are consistent with the underlying theory, replacing unobserved productivity by observables using [1] above:

$$\tilde{a}_{it} = y_{it} - (\alpha_l \cdot l_{it} + \alpha_k \cdot k_{it}) - \tilde{\varepsilon}_{it}$$

which, after some simple manipulations, results in a specification of the following form:

$$l_{it} = \pi_\rho \cdot l_{i,t-1} + \pi_a \cdot y_{it} + \pi_k \cdot k_{it} + \pi_{lk} \cdot k_{i,t-1} - \pi_w \cdot w_{it} + \tilde{\psi}_i + \tilde{\varpi}_{st} + \tilde{e}_{it}$$

The underlying theory implies that productivity impacts positively, and the wage rate negatively, on labor demand, hence we should expect to obtain a positive coefficient on log output and a negative coefficient on the wage variable in the regression. The next step in the analysis is to replace unobserved productivity in the labor equation by the agglomeration variables proposed in the previous subsection, resulting in a specification of the following form:

$$l_{it} = \tau_{\rho} \cdot l_{i,t-1} + \mathbf{x_{jt}c} + \tau_k \cdot k_{it} + \tau_{lk} \cdot k_{i,t-1} - \tau_w \cdot w_{it} + \hat{\psi}_i + \hat{\varpi}_{st} + \hat{e}_{it}$$

Provided productivity impacts on labor growth, we hypothesize that the agglomeration variables in the vector $\mathbf{x_{jt}}$ have qualitatively the same impact on labor growth as on productivity. We remove firm fixed effects by taking first differences, and, as is standard in dynamic panel data models, estimate the parameters using GMM. Further econometric details are discussed in Section 4.

3. Data and descriptive statistics

The source of data in this study is the annual census data on manufacturing establishments with 10 or more workers, collected by the Ethiopian Central Statistic Office (CSA). The full dataset is a 10 years long (1996 to 2005) unbalanced panel comprising 7870 firm/year observations, and covers both private and public manufacturing establishments all over the country. Unfortunately, in 2005, for the first time, CSA fielded a sample survey rather than census. This implies cluster characteristics in the 2005 data, would have to be estimated based on samples, which could lead to inaccuracies. We therefore drop the 2005 data and rely on the nine years (1996-2004) census-based annual panel data in the empirical analysis.

The annual survey instrument by CSA contains a variety of questions covering output, sales (domestic and export), variety of inputs used and costs, employment, wage, other labor costs, and investment etc at establishment level. The data also has detailed establishment level location indicators from region to the smallest administrative location. The region is the higher administrative level. Ethiopia is divided into 11 regions of which two are city administrations; Addis Ababa and Dire Dawa. Zone is the third administrative tier next to the region. Currently, there are about 66 zones in the country, outside the two city regions. The zones are further divided into lower administration levels such as Woreda and Kebelle, the fourth and fifth tiers respectively. The data also identifies establishments by town. The town is not a political administration category but could be regarded as region, zone or woreda depending on the size of the town. For example, the capital city Addis Ababa and Dire Dawa are considered as regions and at the same time towns. The other bigger cities are also zones and at the same time towns.

To assess the agglomeration externalities we need to define the geographical and industrial boundaries of clusters. In this study we define own industry broadly at the 2-digit ISIC level, which results in 8 industries, namely: food and beverage, textile, leather, wood and furniture, paper and printing, chemicals, non-metallic, and metal industries. Different practices with regard to the geographical scope can be identified in the literature. A number of studies take the county or equivalent geographical area as a unit of analysis (for example, Ellison and Glaeser 1997, Henderson 2003, Lall et al. 2004). Fafchamps and El Hamine (2004) use three levels of geographic scope in Morocco (i.e. province, city and commune from largest to smallest accordingly). Others have relied on wider geographical areas for example, Statistical Metropolitan Areas (SMA) in the U.S. We use the lowest level of the location categories as the basis for geographical scope, namely town. In our data we have 101 towns hosting at least one manufacturing establishment.[9]

We next provide an overview of the characteristics and concentration of manufacturing establishments in our data. Figure 1 shows how average firm size and the number of firms have evolved over the 1996-2004 period. Average firm size has fallen from 146 employees in 1996 to 105 employees in 2004. The number of firms, however, has grown from 623 to 997 in over the same period. The fall in average firm size primarily reflects the exit of a small number of very large firms. The median firm size actually increases from 23 to 26 over the period. Figure 2 shows average growth year-by-year growth rates. Post 1999, average annual growth rates have varied between 0 and 5%, and over the entire period is the average growth rate is 2%. Table 1 shows the geographical distribution of manufacturing establishments and employment for the largest 10 towns in Ethiopia. Manufacturing establishment location is highly concentrated in a few urban areas. The top ten towns account for above 75% of the total manufacturing establishments and above 72% of employment. Addis Ababa,

[9] We have also considered using zones rather than towns as the basis for location. The empirical results were similar to those based on town. This is not surprising, given that some major towns are also zones and that there are some towns that dominate other zones.

the capital city, alone takes above half of the country manufacturing establishments and employment. In the last ten years the high concentration in the capital city has declined, in terms of both the number of establishments and employment from about two-thirds in 1996 to about half in 2004. There is a ranking difference across the other towns too. Perhaps the most striking observation is that while the concentration in Addis Ababa is declining, new industry concentration is emerging around the capital city as we can see from the increasing number of towns with asterisk (towns within 100 km from Addis Ababa) by year in Table 1. For reference, the table also shows summary statistics where location is based on zone rather than town.

Table 2 gives the notation, definition, and some summary statistics of the variables used in this study. Output is defined as gross output deflated by industrial output deflators at two-digit level industrial classification. Capital is constructed using the perpetual inventory method.[10] Labor is measured by the sum of permanent and temporary workers the latter adjusted to year equivalent labor. Average number of establishments at the town level is about 5, but the median is only 1. Average number of workers of a given sector is about 618 for town. An average town hosts about 11 total number of manufacturing establishments, with total employment of 3230.

4. Econometric Results

In this section we present our econometric results. In the first sub-section we estimate the effects of the various cluster variables on total factor productivity. In the second part of the section we assess the effects of the agglomeration variables on firm growth, hypothesizing that such effects may operate through productivity.

4.1 Agglomeration and productivity

[10] Specifically, for each firm we took the beginning year capital (when it enters the data set) as a base and constructed capital stock sequentially by adding investment and subtracting sold assets and depreciation. We used different depreciation rates for different types of assets; 8 percent for machinery and equipment, 5 percent for buildings and 10 percent for vehicle and furniture and fixture. Then we derived a new capital stock series by taking the average of the beginning and the end year capital stock for use throughout our analysis.

Table 3 shows GMM estimates of the parameters of our Cobb-Douglas production function, in which cluster size for firm *i* at time *t* is defined as the number of firms in the same sector and town as firm *i*, at time *t*. Alternative measures of cluster size will be considered below. In all specifications shown in Table 3, the factor inputs capital and labor are treated as endogenous while the cluster variables are assumed predetermined.[11] Time dummies and time interacted with sector dummies are included in all specifications. Column 1 shows results for the output production function, with no restrictions imposed on the returns to scale. Two cluster coefficients are statistically significant: that on the dummy for no other firm in the cluster, and that on the log of cluster size. Both coefficients are positive, implying a nonlinear effect of cluster size for very small clusters. With the estimated coefficient on sole operator equal to 1.02 and that on log cluster equal to 0.96, it follows that an increase in cluster size from 1 to 2 firms reduces productivity by 1.02-0.96ln(2) = 0.35 log points or approximately 30% in the cluster. Beyond this point, further increases in cluster size increase productivity, and the initial negative effect is more than balanced out at cluster size 3 (that is, a cluster consisting of 3 firms is predicted to have marginally higher productivity than a cluster with only one firm). Figure 3 shows the predicted productivity-cluster size relationship. The productivity of firms in clusters with six or more enterprises is significantly different from that of firms not operating in clusters, and the point estimate is twice as high. These results suggest that firms stand to gain a lot from being located in places where several similar enterprises operate. Market concentration, as measured by the Herfindahl index in the cluster, appears not to play an important role in this context. Neither do specialization or our crude measure of the intensity of technological acquisition in the cluster.

The estimated coefficient on labor is equal to 0.49 and statistically significant from zero at the 1% level, whereas that on capital is equal to 0.10 but imprecisely estimated. We will shortly discuss our attempts to probe these results further. Based on the outcome of the Hansen specification test, we do not reject the hypothesis that the overidentifying restrictions are valid. Of course this doesn't "prove"

[11] We use as instruments the second and third lag of the growth rates in employment and physical capital, and the first and second lag of the cluster variables in levels. We will consider below the effects of treating the cluster variables as endogenous rather than predetermined.

that our instrumenting strategy is valid, but at least it provides some suggestive evidence that the instruments are not invalid. Consistent with the proposition that the instruments are not invalid, there also is no evidence of second order serial correlation in the differenced residuals.

Estimating production functions in first differences is often problematic. Many authors using such an approach report implausibly low, and imprecise, estimates of the capital coefficient, and decreasing returns to scale (see Griliches and Mairesse, 1997, for a discussion). We face similar issues, as already noted. Weak instruments are often cited as the main problem. A popular cure in the literature is to add moment conditions in levels, producing the System GMM estimator (see Blundell and Bond, 1998, 2000; and Arellano and Bover, 1995). We do not pursue this estimator here, for two reasons. First, when using the System GMM estimator with our data, we obtained fairly strong evidence from standard specification tests that the levels moment conditions were invalid.[12] It would therefore be hard to justify using this estimator on statistical grounds. Second, we want to deal with unobserved firm fixed effects as robustly as possible. The differenced estimator does so by simply eliminating them from the data. The System GMM estimator, in contrast, leaves the fixed effects in the levels residual, making this estimator more demanding in terms of what is required from the instruments.

Recognizing that our estimated returns to scale are likely too low, and that weak instruments are likely the reason, we consider results from a model in which constant returns to scale is imposed on the data.[13] We operationalize this by expressing the production function in capital productivity form, dividing output and labor by capital and regressing log of the output capital ratio on the log labor-capital ratio and the other variables in the model. The estimated coefficient on the labor-capital ratio is interpretable as the labor coefficient β_l in the production function (1), with $\beta_k = 1 - \beta_l$. From a statistical point of view, the main advantage is that there is one less endogenous variable, and so the

[12] For example, a criterion based test comparing the System GMM estimator to the Differenced GMM estimator for the specification in Table 3, column 1, indicated the levels moment conditions are rejected at the 5% level.
[13] Nickell (1996) proposed such an approach, in view of estimation problems such as those just discussed.

precision of the estimates should improve. More substantively, this procedure helps us assess whether the results obtained from the freely estimated production function are robust.

Results for the model with constant returns to scale imposed, and the instrument set unchanged, are shown in Table 3, column 2. The previous results prove quite robust. The estimated coefficients on cluster size and the dummy for no other firm in the cluster change only marginally, and remain highly statistically significant. The conclusions drawn above thus remain the same. None of the other cluster variables is significant. The estimated labor coefficient is 0.78, thus quite a bit higher than in the previous model. The implied capital coefficient is 0.22. These estimates appear sensible and are certainly in line with previous work in the area (Söderbom and Teal, 2004; Frazer, 2005). The specification tests provide no evidence that the model is mis-specified.

The results above are all based on a two-factor output production function. As discussed in Section 2 there is no particular reason why one might prefer such a specification to a two-factor value-added production function, as both can be derived from the same underlying, structural, production function under the same assumptions. In our data the correlation between differenced log output and differenced log value added is 0.72 - high, but sufficiently below unity to warrant separate analysis of the value added production function in order to see if the main results are robust. In columns 3 and 4 of Table 3 we thus show results for models in which value-added is the dependent variable instead of output, without, and with, constant returns to scale imposed. The results for the cluster variables are similar to those reported above. Importantly, the coefficient on cluster size remains positive, quantitatively large, and statistically highly significant. One difference compared to the output results are that the coefficient on the dummy for no other firm in the cluster is no longer statistically significant at conventional levels, weakening the evidence that an increase in cluster size from one to two firms reduces productivity. Furthermore, there is some evidence (at the 5% level but not at the 1% level) of second order serial correlation in the differenced residuals. The latter result suggests that the levels residual is serially correlated, which may pose a problem for our strategy of constructing instruments based on lags. The Hansen specification tests suggest no strong evidence that the overidentifying restrictions are invalid, however, so the problem may not be overly severe.

The cluster definition underlying the results in Table 3 is narrow: only firms in the same location and same sector (at the same point in time) are considered part of a particular firm's cluster. However, agglomeration effects such as information-sharing, organizational innovations, better access to labor, etc. are not necessarily specific to the sector in which they originate. Furthermore, it could be argued that the entry of own-sector firms is somewhat of a mixed blessing from the point of view of the individual firm; there may well be agglomeration effects which raise productivity and profitability, but there may also be negative short-run effects due to increased competition.[14] The entry of firms in other sectors probably has a weaker effect on competition. In Table 4 we show results for specifications in which the cluster is defined as consisting of firms in the same location in all sectors except the firm's own sector. We find somewhat different results as a consequence of using the alternative cluster definition. The evidence that cluster size impacts on total factor productivity is now weaker than previously. Throughout the regressions shown in Table 4, the estimated coefficient on cluster size is positive, but it is only statistically significant in the output production functions, and only at the 10% level. This suggests that agglomeration effects across sectors may be weaker than intra-sector effects. There is now fairly strong evidence that the degree of concentration in the firm's location, measured by the Herfindahl index, matters. In all four regressions reported in Table 4 the estimated coefficient on the Herfindahl index is negative and significant at the 5% level, indicating that high concentration in the location has an adverse effect on productivity. There is no evidence whatsoever that the entry of firms into clusters that were previously occupied by only one firm is bad for productivity, as reflected in the negative and insignificant coefficient on sole operator. Finally, there are some signs that these models are mis-specified. Based on the Hansen specification tests, we can reject the null hypothesis at the 5% level in one case, in the other three cases at the 10% level. We

[14] For example, suppose the size of the local market for a certain manufactured product is approximately fixed, in the short term. As the number of own-sector firms in the town increases, each firm gets a smaller share of the pie. This will reduce the value of sales conditional on inputs, at least in the short term, before firms have adjusted their inputs.

conclude from this that the cluster definition based on own-sector firms is to be preferred, and in the remainder of the paper this is what we shall adopt.

We now consider an alternative definition of cluster size, using total employment in the cluster (excluding that of the own firm) instead of the total number of enterprises. Results are shown in Table 5. In all models reported, the estimated coefficient on cluster employment is positive, in line with earlier findings indicating that firms benefit from being located in large clusters. For the output production functions, this effect is significant at the 5% level whereas for the value-added models the estimated coefficient is insignificant. The value added results should be interpreted with caution as the Hansen tests and the tests for second order serial correlation indicate rejection at the 5% level, suggesting the value added models are mis-specified. No other cluster coefficient is statistically significant in any of the models shown. As for the coefficients on the factor inputs the pattern is similar to that established earlier, in the sense that it is proving hard to estimate the production function very precisely unless we impose constant returns to scale.

The evidence considered so far indicates that the frequency-based measure of cluster size fits the data better than the employment-based measure. Henderson (2003) reaches a similar conclusion. There is also some evidence that the value-added model is mis-specified, but there is no such evidence for the output model. We now report results for a number of robustness checks for the output constant returns to scale model considered in Table 3, column 2.

We begin by testing the effects on the results of altering the way in which we control for heterogeneity in productivity growth across sectors. Recall that, in all previous regressions, we include time dummies and time interacted with sector dummies. This approach is flexible in the sense that productivity growth is allowed to differ across sectors. However it is potentially restrictive in the sense that the difference in average productivity growth across sectors is assumed constant over time. We now generalize the way in which we control for sector-specific time trends further, by including a full set of interaction terms between the sector dummies and the time dummies.[15] As can be seen in column 1 in Table 6, all the main results for the output production function documented above are robust. The coefficient on cluster size is positive and significant, as is the coefficient on the dummy for no other firm in the cluster. Thus, entry of own-sectors into the cluster tends to raise productivity, except for the special case where there is only one firm in the cluster initially.

Next, we investigate whether treating the cluster variables as endogenous rather than predetermined makes a difference.[16] The model in shown in column 2 of Table 6 is thus the same as that in Table 3, col. 2, except that we have now excluded from the instrument set the first lag of the cluster variable, on the grounds that this will be correlated with the differenced residual if the cluster variables are endogenous. The point estimate of the coefficient on cluster size hardly changes at all, though as expected the associated standard error increases somewhat. The estimated coefficient is nevertheless significant at the 5% level. The coefficient on no other firm in cluster becomes wholly insignificant, however, weakening the evidence that productivity falls as cluster size increases from one to two. Furthermore, testing the null hypothesis that the cluster variables are predetermined by comparing the Hansen test statistic for the current model with that of the model in Table 3, col.2, we find that we cannot reject the null hypothesis at the 10% level.

We now investigate whether there is any evidence that the effect of cluster size varies depending on how technologically advanced the firm is. It might be that the technological spillovers – if that is an important source of agglomeration effects – matter most for firms with a relatively sophisticated technology. As a crude measure of how technologically advanced a firm is we use the labor-capital ratio, on the grounds that technologically more sophisticated firms are likely to use more capital per worker. Column 3 in Table 6 shows the results for the baseline model with an interaction term between the labor-capital ratio and cluster size added as an explanatory variable. If the cluster effect is stronger amongst those with more capital per labor (and hence a lower labor-capital ratio), this would

[15] We thank Jean-Luis Arcand for suggesting this approach.
[16] Following Wooldridge (2002), endogeneity is taken to imply that an explanatory variable x_{it} is contemporaneously correlated with the residual.

show up here as a negative coefficient on the interaction term. We find, however, that the coefficient is close to zero and totally insignificant. There is thus no evidence that the cluster size effect varies with the capital intensity of the firm. Whether more or less technologically advanced, firms appear to benefit from being located in an environment in which several similar enterprises operate.

Recall from Section 2 that approximately half the sample is made up by firms located in the capital city, Addis Ababa. We now investigate whether the results are sensitive to whether these firms are included or not. Column (4) shows results for the baseline model with firms in Addis Ababa excluded. The estimated coefficient on cluster size is equal to 0.62, thus somewhat lower than previously. The coefficient is significant at the 10% level. Thus, while there is some evidence that the cluster size effect on productivity is smaller outside the capital city, the previous results are not driven solely by the Addis sub-sample. Finally, we ask if the result that cluster size impacts positively on productivity is robust in a more parsimonious model than those considered above. In column 5 of Table 6 we have dropped all the cluster variables from the model except cluster size. The instrument set has changed accordingly, now consisting only of cluster size, lagged factor input growth, and the time trend variables. We find that the main result is indeed robust: the estimated coefficient on cluster size is now just above unity and statistically significant at the 1% level.

Short-term enterprise growth

Our main conclusion based on the empirical analysis above is that the agglomeration of own-sector firms in a particular location causes productivity gains for the individual firm. We now ask if there is any evidence that such productivity gains have knock-on effects on labor demand and thus enterprise growth. Table 7 shows GMM estimates of the parameters of the dynamic labor equations discussed in Section 2. Column 1 shows the results for the specification in which we replace unobserved productivity by output and the factor inputs as implied by the production function [1]. The wage variable is treated as predetermined, thus we use wages lagged one and two periods as instruments. Output, capital and lagged employment are assumed correlated with the differenced residual (hence econometrically endogenous), and so we use lags of these variables dated t-2 and t-3 as instruments.

We obtain a positive and highly significant coefficient on log output, which suggests that a positive productivity shock raises employment growth in the short term. Given that cluster size impacts positively on productivity, this suggests agglomeration impacts on growth via productivity. We investigate this using a more direct approach below. The estimated coefficient on lagged employment is equal to 0.15, suggesting fairly rapid adjustment of labor. The coefficient is significant at the 5% level. The wage coefficient is statistically significant at the 1% level and, consistent with the underlying theory, negative.

In column (2) we add the agglomeration variables to the labor equation whilst omitting output, hypothesizing that agglomeration impacts on growth via productivity. The coefficient on cluster investment is positive and significant at the 5% level, suggesting that firms located in clusters in which there is a lot of investment in physical capital grow relatively fast. The coefficient on log cluster size is positive but not significant. In column (3) we drop all agglomeration variables for which the associated coefficient has a t-value less than one. We do this to see if the standard errors on the remaining coefficients fall as a result. That is indeed the case. The coefficient on cluster size is now significant at the 10% level. The point estimate suggests that a 1% increase in cluster size raises growth in the short term by 0.20%. The coefficient on cluster investment remains positive and significant at the 5% level. In column (4) we add back the output variable to the specification whilst retaining the relevant cluster variables, in order to see if cluster characteristics impact on growth conditional on productivity. Consistent with the idea that the cluster variables affect growth through productivity, all the cluster coefficients become smaller, and much less significant, as a result of including output in the model. This lends further support to the hypothesis that the cluster size effects obtained in (3) can be interpreted as a productivity effect.

In columns (5)-(7) we show results from robustness analysis. In column (5) we generalize the time trend and include a full set of interaction terms between sector and time dummies. The point estimates of the cluster coefficients change little as a result, though the standard errors increase somewhat. We conclude that capturing heterogeneity in growth rates across sectors by allowing for sector-specific linear time trends is not inappropriate. In column (6) we drop the firms located in Addis Ababa. If anything, the effects of cluster size and cluster investment become stronger as a result of excluding the firms located in the capital city. In column (7), finally, we consider the effects of treating the agglomeration variables as endogenous rather than predetermined. The point estimate of the coefficient on cluster size changes very little compared to the previous specifications, however that on cluster investment changes a lot and now is very close to zero. This suggests cluster investment may be correlated with firm specific shocks to employment growth. As expected, the standard errors on both cluster coefficients increase as a result of treating these variables as endogenous.

5. Concluding remarks

The main result in our productivity analysis is that there are positive effects of the agglomeration of firms belonging to the same industrial sub-sector, possibly reflecting knowledge spillovers. The agglomeration of firms belonging to different industrial sub-sectors is positively correlated with own productivity, but the effect is generally not significant. We thus find that physical proximity to own-sector firms is more important for productivity than proximity to firms in other industrial sectors. This result is a common finding in advanced economies. The fact that we can identify a very significant effect even in poor and undifferentiated Ethiopia suggests that agglomeration forces are quite strong. We do not find that market concentration, specialization, or technological acquisition have any significant productivity effect when using the narrower definition of cluster, but concentration as measured by the Herfindahl index has a weakly significant effect when we use the broader cluster definition. The results are similar but considerably weaker when we switch from the cluster definition using number of firms to using cluster employment. Frequency based measures of agglomeration thus fit the data better than employment based measures, which is consistent with the hypothesis that firms learn from observing their neighboring entrepreneurs experimenting.

We do a series of robustness tests and our main results carry through with small changes. A common result in the literature is that agglomeration economies matter more for high-tech than low-tech industries (Henderson, 2003, p. 15). However, we no evidence that the cluster size effects varies with firms' capital intensity. We also find that the results are not driven by the sub-sample of firms located in Addis Ababa.

Finally, we investigate whether productivity effects affect labor demand and thus also enterprise growth. Using a dynamic labor demand equation, we find a significant productivity effect on labor demand, suggesting that the conventional view that agglomeration affects growth via its effect on productivity applies. When tested directly, we find some evidence that cluster size and cluster investment impact on short term employment growth. Again, results are robust to excluding the firms located in Addis Ababa. Agglomeration thus seems to contribute to firm growth in the short term, and larger firms in the long term. Overall, our analysis thus implies that if policy makers can design policies that encourage the agglomeration of firms, this will create new jobs, raise productivity, and improve the performance of the manufacturing sector in Ethiopia.

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Figure 1: Average Employment and Number of Firms: 1996-2004

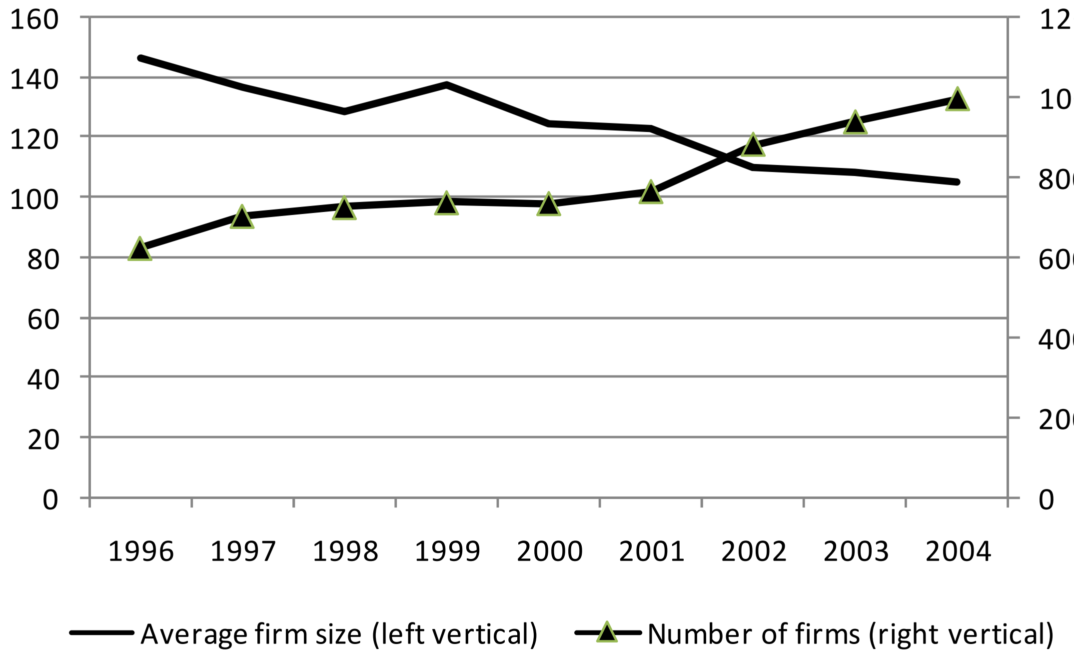
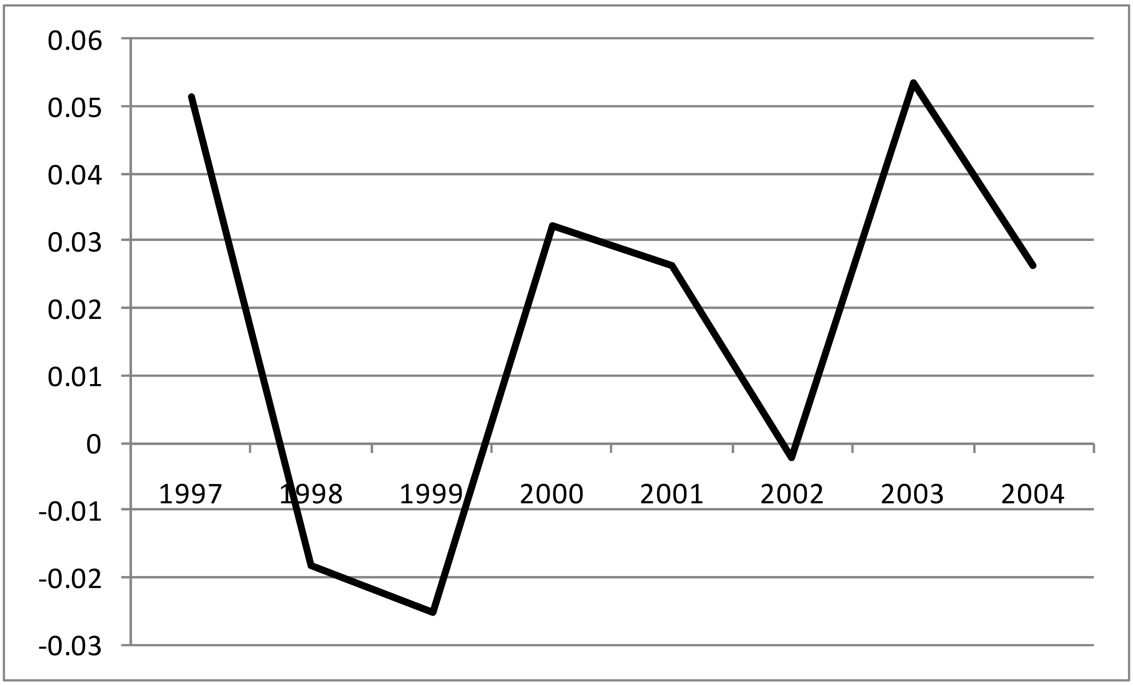
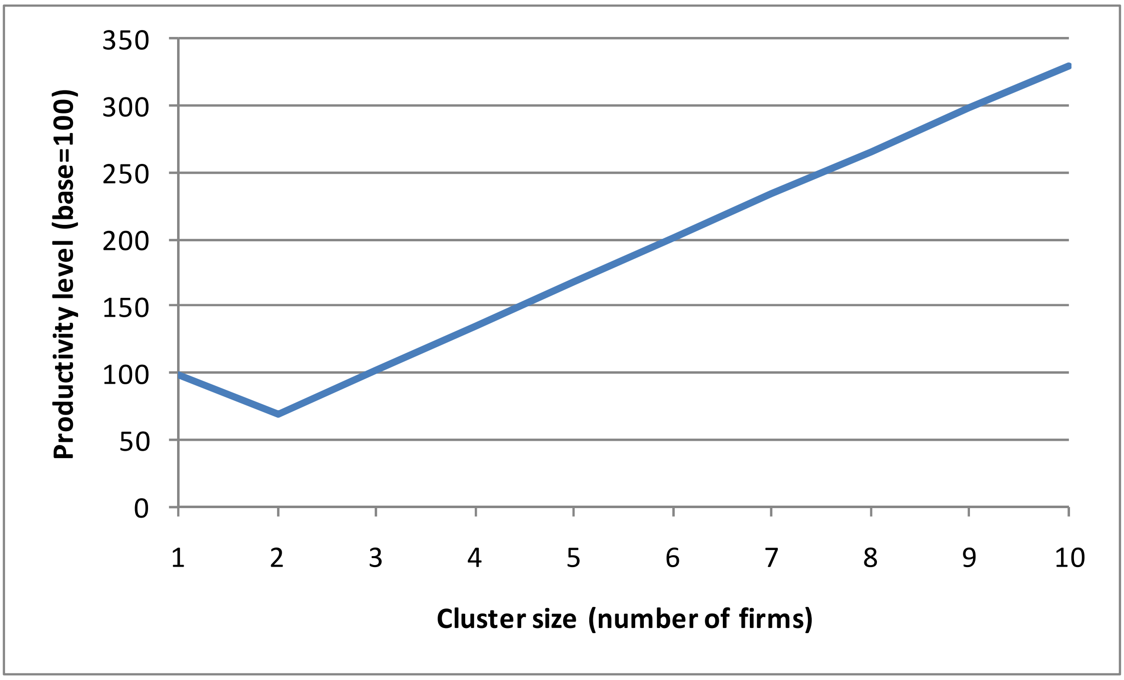


Figure 2: Average Employment Growth Rates, Year-to-Year



Note: The graph shows unweighted averages of log differences in employment across firms.

Figure 3. Predicted effect of cluster size on enterprise productivity



Note: Predictions are based on the estimates shown in Table 3, col.1. The kink in the graph is driven by the coefficient on dummy for sole operator in cluster.

Table 1: Geographical concentration of manufacturing establishments in Ethiopia

1996			2000			2004		
Towns by rank	# of firms	employ-ment sum	Towns by rank	# of firms	employ-ment sum	Towns by rank	# of firms	employ-ment sum
Addis Ababa	418	55054	Addis Ababa	457	49063	Addis Ababa	548	56086
Dire Dawa	25	6395	Awasa	23	3374	Awasa	32	2922
Bahr Dar	16	2995	Dire Dawa	22	6539	Mekelle	29	1830
Awasa	15	2900	Nazreth*	19	1375	Bahr Dar	23	2684
Nazreth*	14	1371	Debre Zeit*	17	1660	Burayu*	22	1415
Jimma	12	404	Jimma	15	342	Dire Dawa	22	4092
Mekelle	10	265	Mekelle	14	1521	Nazreth*	22	1818
Debre Zeit*	7	1132	Bahr Dar	13	2245	Debre Zeit*	19	2915
Harara	7	1211	Burayu*	8	201	Sebeta*	17	1814
Dessie	6	318	Gondar	8	1066	Dessie	15	406
Top 10 towns	530	72045		596	67386		749	75982
% of top 10 towns	85.2	79.1		82.6	73.6		76.3	72.6
% of Addis Ababa	67.2	60.4		63.3	53.6		55.8	53.6
Total	622	91096		722	91528		982	104681

Note that the towns with asterisk (*) are located no more than 100 km distance from Addis Ababa.

Table 2: Definition and summary statistics of the relevant variables

Variables	Notation	mean	median	(sd)
ln(output)	ln(y)	13.8	13.4	2.2
ln(capital)	ln(K)	13.1	13.1	2.6
ln(labor)	ln(L)	3.6	3.3	1.4
ln(intermediates)	ln(M)	13.2	12.9	2.2
a) Town				
Number of establishments in the sector and town	N_{ij}	4.98	1	14.24
Total number of firms in the town	N_i	11.09	2	56.77
Sum of employment in the sector and the town	L_{ij}	618.26	60	1733.04
Sum of employment in the town of all sectors	L_i	3230.70	921	7068.08
Export dummy	X_{kd}	0.09	0	0.26
Number of exporters in the town and given sector	X_{ij}	0.23	0	0.78
Number of sectors in the town	M_i	3.66	3	2.34
Number of positive investment in the town & sector	I_{ijt}	2.37	1	6.39
Harfindahl index of sales	$\sum_k \left(\frac{S_k}{S_{ijt}}\right)^2$	0.80		0.29
Specialty index in the town	$\sum_j \left(\frac{L_{ijt}}{L_{it}} - \frac{L_i}{L}\right)^2$	0.50	0.55	0.29
b) Zone				
Number of establishments in the sector and zone	N_{ij}	6.51	2	16.12
Total number of firms in the zone	N_i	20.7	5	76.5
Sum of employment in the sector and the zone	L_{ij}	804.3	76.5	2027.8
Sum of employment in the zone of all sectors	L_i	2552.5	270.5	8710.7
Export dummy	X_{kd}	0.08	0.0	0.25
Number of exporters in the zone in the given sector	X_{ij}	0.30	0.0	0.94
Number of sectors in the zone	M_i	4.63	4.0	2.35
Number of positive investment in the zone & sector	I_{ijt}	3.09	1.0	7.27
Harfindahl index of sales	$\sum_k \left(\frac{S_k}{S_{ijt}}\right)^2$	0.69	0.84	0.33
Specialty index in the zone	$\sum_j \left(\frac{L_{ijt}}{L_{it}} - \frac{L_i}{L}\right)^2$	0.31	0.27	0.22

Note that L, S, N, and M stands for number of employment, total sales, number of establishments, number of sectors respectively. k, i, j, t also denotes firm, location, sector, and time respectively.

Table 3: Agglomeration and Productivity: Baseline GMM Results

	(1) log Output	(2) log Output / Capital	(3) log Value-Added	(4) log Value-Added / Capital
log Employment	0.486		0.782	
	(4.12)**		(3.11)**	
log Capital	0.104		-0.088	
	(1.28)		(0.22)	
log Employment / Capital		0.777		0.893
		(3.94)**		(3.97)**
log Cluster size	0.964	0.914	1.222	1.157
(own-sector firms in location)	(3.92)**	(3.70)**	(3.05)**	(2.99)**
Speciality index	0.006	0.006	0.002	0.002
	(1.44)	(1.34)	(0.50)	(0.46)
Herfindahl index	0.172	0.082	-0.013	-0.123
	(0.74)	(0.35)	(0.03)	(0.30)
No other firm in cluster	1.015	0.878	0.836	0.654
	(2.68)**	(2.30)*	(1.22)	(1.02)
Proportion of firms in	0.121	0.161	0.224	0.230
cluster that invest	(0.81)	(1.07)	(0.96)	(1.00)
Hansen test (p-value)(1)	0.41	0.35	0.13	0.15
m_1 (p-value)(2)	0.00	0.00	0.00	0.00
m_2 (p-value)(3)	0.83	0.71	0.04	0.04
Number of firms	1084	1084	1084	1084
Number of observations	3715	3715	3715	3715

Note: All results are obtained using a 2-step GMM estimator. The models are estimated in first differences, in order for the firm fixed effects to be eliminated. Time dummies and sector specific time trends are included in all regressions but results are not reported in order to conserve space. The numbers in ( ) are t-statistics and significance at the one per cent, five per cent and ten per cent level is indicated by *, ** and + respectively. The covariance matrix is computed using the method proposed by Windmeijer (2005), which takes into account the fact that the weight matrix used in the second step of the GMM estimator is estimated in the first step (ignoring this typically leads to a downward bias in the estimated standard errors; see Arellano and Bond, 1991). The instrument set consists of employment and physical capital differenced and lagged 2 and 3 periods; the cluster variables in levels lagged 1 and 2 periods; and the time dummies and sector-specific time trends.

(1) Tests for the validity of the overidentifying restrictions.

(2) Tests the null hypothesis that the differenced residuals in periods t and t-1 are uncorrelated.

(3) Tests the null hypothesis that the differenced residuals in periods t and t-2 are uncorrelated.

Table 4: Agglomeration and Productivity: Testing for Inter-Sector Effects

	(1) log Output	(2) log Output / Capital	(3) log Value-Added	(4) log Value-Added / Capital
log Employment	0.649		0.432	
	(3.08)**		(1.32)	
log Capital	0.295		0.450	
	(1.00)		(0.90)	
log Employment / Capital		0.657		0.494
		(3.47)**		(1.71)+
log Cluster size	0.353	0.371	0.361	0.358
(non-own sector firms in location)	(1.67)+	(1.78)+	(0.97)	(0.97)
Speciality index	0.004	0.004	0.001	0.001
	(0.76)	(0.74)	(0.12)	(0.12)
Herfindahl index	-0.502	-0.517	-1.022	-1.045
	(1.98)*	(2.13)*	(2.01)*	(2.14)*
No other firm in cluster	-0.449	-0.479	-1.110	-1.125
	(1.36)	(1.48)	(1.77)+	(1.90)+
Proportion of firms in	0.198	0.197	0.039	0.048
cluster that invest	(1.27)	(1.26)	(0.14)	(0.18)
Hansen test (p-value)	0.05	0.07	0.06	0.07
m_1 (p-value)	0.00	0.00	0.00	0.00
m_2 (p-value)	0.60	0.59	0.05	0.05
Number of firms	1084	1084	1084	1084
Number of observations	3715	3715	3715	3715

Note: All results are obtained using a 2-step GMM estimator. The models are estimated in first differences, in order for the firm fixed effects to be eliminated. t-statistics and significance at the one per cent, five per cent and ten per cent level is indicated by *, ** and + respectively. See Table 3 for further details.

Table 5: Agglomeration and Productivity: Employment as a Measure of Cluster Size

	(1) log Output	(2) log Output / Capital	(3) log Value-Added	(4) log Value-Added / Capital
log Employment	0.615		0.824	
	(3.30)**		(3.39)**	
log Capital	0.120		-0.183	
	(0.42)		(0.45)	
log Employment / Capital		0.708		0.968
		(3.54)**		(4.59)**
log Cluster size (total employment, own-sector firms)	0.254	0.250	0.148	0.134
	(2.51)*	(2.44)*	(0.89)	(0.80)
Speciality index	0.007	0.007	0.003	0.003
	(1.34)	(1.35)	(0.72)	(0.66)
Herfindahl index	-0.266	-0.332	-0.490	-0.571
	(1.02)	(1.33)	(1.16)	(1.36)
No other firm in cluster	0.766	0.694	0.040	-0.117
	(1.48)	(1.33)	(0.05)	(0.15)
Proportion of firms in cluster that invest	0.018	0.038	0.108	0.131
	(0.12)	(0.24)	(0.44)	(0.54)
Hansen test (p-value)	0.15	0.19	0.00	0.00
m_1 (p-value)	0.00	0.00	0.02	0.02
m_2 (p-value)	0.43	0.41	0.03	0.02
Number of firms	1084	1084	1084	1084
Number of observations	3715	3715	3715	3715

Note: All results are obtained using a 2-step GMM estimator. The models are estimated in first differences, in order for the firm fixed effects to be eliminated. t-statistics and significance at the one per cent, five per cent and ten per cent level is indicated by *, ** and + respectively. See Table 3 for further details.

Table 6: Agglomeration and Productivity: Further Robustness Checks

	(1) log Output / Capital	(2) log Output / Capital	(3) log Output / Capital	(4) log Output / Capital	(5) log Output / Capital
log Employment / Capital	0.822	0.841	0.964	0.573	0.695
	(3.94)**	(3.82)**	(3.83)**	(2.33)*	(2.97)**
log Cluster size	0.756	0.904	1.075	0.621	1.213
(own-sector firms in location)	(3.06)**	(2.47)*	(1.63)	(1.75)+	(3.00)**
Speciality index	0.003	0.009	0.006	0.005	
	(0.72)	(1.15)	(1.24)	(1.77)+	
Herfindahl index	0.187	-0.311	0.153	0.223	
	(0.80)	(0.50)	(0.64)	(0.77)	
No other firm in cluster	0.831	-0.119	0.912	0.800	
	(2.24)*	(0.13)	(2.34)*	(1.51)	
Proportion of firms in	0.143	-0.413	0.123	0.203	
cluster that invest	(0.99)	(0.96)	(0.82)	(1.07)	
log Cluster size x log L/K			0.019		
			(0.28)		
Hansen test (p-value)	0.22	0.72	0.81	0.15	0.96
m_1 (p-value)	0.00	0.00	0.00	0.00	0.00
m_2 (p-value)	0.92	0.86	0.75	0.72	0.86
Note	Generalizes sector time trend	Cluster variables endogenous	Interacts cluster with L/K	Addis Ababa excluded	Parsimonious specification & IV set
Number of firms	1084	1084	1084	425	1085
Number of observations	3715	3715	3715	1383	3721

Note: All specifications can be viewed as testing the robustness of the results shown in Table 3, col. 2. In (1), we include sector-time dummies instead of a linear sector specific time trends. In (2) we remove the first lag of the cluster variables from the instrument set, thus treating the cluster variables as endogenous rather than predetermined. In (3) we add a term interacting log capital intensity and log cluster size. In (4) we drop all cluster variables from the model and the instrument set except cluster size. All results are obtained using a 2-step GMM estimator. The models are estimated in first differences, in order for the firm fixed effects to be eliminated. The numbers in ( ) are t-statistics and significance at the one per cent, five per cent and ten per cent level is indicated by *, ** and + respectively. The covariance matrix is computed using the method proposed by Windmeijer (2005), which takes into account the fact that the weight matrix used in the second step of the GMM estimator is estimated in the first step.

Table 7: Agglomeration and Employment Dynamics: GMM Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log Employment$_{t-1}$	0.150	0.111	0.135	0.136	0.115	0.014	0.148
	(2.51)*	(1.95)$^{+}$	(2.37)*	(2.60)**	(2.15)*	(0.22)	(2.31)*
log Capital$_{t-1}$	0.023	0.031	0.025	0.025	0.031	-0.019	0.019
	(0.85)	(0.98)	(1.01)	(0.90)	(1.02)	(0.31)	(0.76)
log Output$_t$	0.192			0.145			
	(3.27)**			(3.04)**			
log Capital$_t$	-0.043	-0.078	-0.061	-0.051	-0.075	-0.011	-0.046
	(1.04)	(2.17)*	(1.83)	(1.38)	(2.00)*	(0.12)	(1.26)
log Wage$_t$	-0.387	-0.378	-0.375	-0.401	-0.393	-0.241	-0.350
	(6.05)**	(6.48)**	(6.44)**	(6.65)**	(7.23)**	(3.37)**	(5.99)**
log Cluster size		0.146	0.196	0.120	0.162	0.211	0.206
(own-sector firms in location)		(1.17)	(1.78)$^{+}$	(1.02)	(1.43)	(2.13)*	(1.45)
Proportion of firms in		0.211	0.181	0.136	0.166	0.169	0.028
cluster that invest		(2.55)*	(2.27)*	(1.83)$^{+}$	(2.05)*	(2.31)*	(0.14)
No other firm in cluster		0.371	0.299	0.162	0.236	0.192	0.097
		(1.42)	(1.97)*	(1.07)	(1.59)	(1.57)	(0.38)
Speciality index		0.000					
		(0.60)					
Herfindahl index		0.128					
		(0.76)					
Hansen test (p-value)	0.10	0.56	0.45	0.42	0.61	0.46	0.36
m_1 (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
m_2 (p-value)	0.82	0.54	0.62	0.93	0.73	0.23	0.73
Note	Output, not cluster vars	Cluster vars, not output	Parsimonious cluster vars	Output & cluster vars	Generalized time trend	Addis Ababa excluded	Cluster vars endogenous
Number of firms	698	698	698	698	698	258	698
Number of observations	2283	2281	2283	2283	2283	854	2283

Note: The dependent variable is log employment. All results are obtained using a 2-step GMM estimator. The models are estimated in first differences, in order for the firm fixed effects to be eliminated. Time dummies and sector specific time trends are included in all regressions. The numbers in ( ) are t-statistics. Significance at the one per cent, five per cent and ten per cent level is indicated by *, ** and + respectively. The covariance matrix is computed using the method proposed by Windmeijer (2005). The wage variable is treated as predetermined, thus we use wages lagged 1 and 2 periods as instruments. Output, capital and lagged employment are assumed correlated with the differenced residual (hence econometrically endogenous), and so we use lags of these variables dated t-2 and t-3 as instruments. The cluster variables are assumed predetermined except in (7).