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See table of contents

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Article abstract

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MANUFACTURING GROWTH AND AGGLOMERATION EFFECTS*

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ABSTRACT – This paper investigates the effect of location-specific competition and diversity on manufacturing growth. Using detailed manufacturing data from Morocco, we find strong and robust evidence of agglomeration effects: competition is good for growth but diversity is not. However, in our study country these effects do not appear to be channelled through productivity or wages. First, agglomeration variables have opposite effects on growth and on individual firm productivity. Second, controlling for productivity directly does not reduce the significance or magnitude of agglomeration variables. In the study country, agglomeration variables measure something that is relevant for manufacturing growth, but it is not productivity. We also find that a rise in average productivity raises subsequent employment and investment, but has no effect on firm entry and exit.

INTRODUCTION

Since Marshall, agglomeration externalities have long attracted the attention of economists (e.g., Henderson, 1988; Fujita, Krugman and Venables, 1999) and geographers alike (e.g., Isard, 1956; Jacobs, 1969; Dicken and Lloyd, 1990). Various sources of externalities have been hypothesized in the literature. Some are thought to raise the productivity of individual firms directly, for instance through the sharing of technological or market-related information (e.g., Arrow, 1962; Glaeser, Kallal, Scheinkman, and Shleifer, 1992). Others are believed to raise profits by reducing transport costs, for example because of closer proximity to consumers and input providers (e.g., Krugman, 1991; Rodriguez-Clare, 1996). The first case corresponds to Marshallian externalities, the second to pecuniary externalities.

Much of the empirical literature on agglomeration externalities focuses on employment growth (e.g., Glaeser *et al.*, 1992; Ellison and Glaeser, 1997; Henderson,

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1997; Combes, 2000; Bun and El Makhloufi, 2007), with the exception of Combes, Magnac and Robin (2004) who also look at firm entry and exit. In order to disentangle pure locational advantages from agglomeration effects, the literature has relied on dynamic panel analysis whereby sectoral employment growth is regressed on proxy variables capturing agglomeration externalities that vary across locations. Panel analysis offers the advantage of controlling for time-invariant location effects, such as geographical advantage. Using this approach, agglomeration effects have been shown to be a strong determinant of employment growth (e.g., Glaeser *et al.*, 1992; Henderson, 1997; Combes, 2000; Bun and El Makhloufi, 2007) and, more recently, of firm entry (e.g., Combes *et al.*, 2004). All these studies assume that agglomeration factors affect manufacturing performance through their effect on productivity, prices, and costs. But, to our knowledge, this has never been tested formally.

This paper examines how the introduction of productivity and wage shock measures in dynamic firm growth and entry regressions affects the coefficients of agglomeration variables. Productivity and wage shock measures are constructed from a large exhaustive panel dataset on individual manufacturing firms at a disaggregated geographical level. Using the same data, Fafchamps and El Hamine (2017) have shown that agglomeration effects affect the total factor productivity of individual firms and the wages they pay their employees. If variables supposed to proxy for agglomeration externalities influence firm growth and entry via productivity and wages, the inclusion of direct – albeit imperfect – measures of productivity and wages should reduce the magnitude of their coefficient. Results contradict this conjecture: although productivity and wage shocks are shown to have a strong effect on employment growth and firm entry, this effect is quite distinct from standard agglomeration variables. We also find that agglomeration variables have an effect on employment growth and firm entry that is quite different from the effect they have on firm productivity and wages. It therefore appears that agglomeration variables in dynamic employment growth regressions measure something else than productivity or wages.

This paper is organized as follows. Our testing strategy is described in Section 1, in relation to the existing literature. The data are presented in Section 2, together with some descriptive statistics. Econometric analysis is presented in Section 3.

1. Testing Strategy

There is a large literature on agglomeration externalities, much of it focusing on manufacturing. The theoretical literature is particularly well developed and has identified many different types of agglomeration effects, some negative (e.g., congestion), some positive (e.g., shared infrastructure). Alfred Marshall, subsequently followed by Arrow (1962) and Romer (1990), identified knowledge spillover as an important source of externalities. To the extent that knowledge is transferred more easily through direct human contact, local information sharing is thought to give rise to agglomeration externalities of the 'Silicon Valley' type. The shared information need not be on technology; it may also include business opportunities or market relevant knowledge (e.g., Rauch and Casella,2003; Fafchamps, El Hamine and Zeufack, 2008).

Different views on what shared information is relevant and how it is exchanged have given rise to different theories regarding the nature of agglomeration effects. One view, attributed to Marshall, Arrow and Romer and hence referred to as the MAR hypothesis by Combes (2000), claims that monopoly and market power are associated with more innovation and hence with larger externalities. The opposite view is championed by Porter (1990) who argues that monopolies are stultifying and that it is competition that spurs innovation and growth. Both these hypotheses are seen as emphasizing externalities within a sector. In contrast, Jacobs (1984) argues that it is the diversity of industries within cities that is a source of externalities, as industries borrow ideas from each other. The empirical evidence is contradictory. Using US data, Glaeser *et al.* (1992) find in general that local competition and urban diversity, but not specialization, encourage employment growth. In contrast, Henderson (1997) finds that both specialization and diversity have positive effects on firm growth but that the former is larger. Using French data, Combes (2000) finds the opposite result that competition and specialization reduce employment growth while diversity is negative for most industries and positive for services.

Pecuniary externalities have also been proposed as possible explanation for spatial concentration (e.g., Henderson, 1988; Fujita *et al.*, 1999). For instance, in a large labor market, it is easier and faster for employers to find the specialized manpower they need. This phenomenon is called thick labor market externalities by Glaeser *et al.* (1992). Forward and backward linkages as initially proposed by Hirschman (1958) are another possibility. Rodriguez-Clare (1996), for instance, construct a model where a larger market triggers entry in intermediate input production, thereby generating gains from specialization (e.g., Ciccone and Matsuyama, 1996; Fafchamps and Helms, 1996; Fafchamps, 1997). Market size also matters. Krugman (1991), for instance, illustrates how proximity to larger market may attract industries if transport costs are neither too high nor too low. In this paper, we examine both types of externalities.

The empirical literature on externalities and industrial development remains unsettled (e.g, Tybout, 2000). Glaeser *et al.* (1992), for instance, conclude that competition and diversity favor firm growth. In contrast, Henderson (1997) and Desmet and Fafchamps (2005) conclude that own-sector externalities are much stronger than those generated by other sectors. In his study of French manufacturing and services, Combes (2000) concludes that competition and total local employment have a negative effect on firm growth while Bun and El Makhloufi (2007) concludes that diversity has a positive effect but competition a negative one. Using a different methodology, Ciccone and Hall (1996) find that employment density increases average labor productivity.

Combes *et al.* (2004) argue that contradictory results may be driven by slight differences in methodology. They insist that a consistent set of regressors needs to be used to obtain meaningful results. Using a set of agglomeration variables similar to that of Combes *et al.* (2004), Fafchamps and El Hamine (2017) use firm-level data to provide evidence of a significant effect on productivity and wages. They find that returns to specialization are strong and large in magnitude and that the net effect of competition on productivity and wages tends to be negative. Their analysis shows that competition tends to lower wages, probably because of thick labor market externalities. They also find some limited evidence in favor of the diversity argument put forth by Jacobs (1984). Thompson (2004) shows that input-output linkages matter for agglomeration externalities.

In this paper we seek to understand the growth of manufacturing over time. Probably due to data limitations, earlier papers have followed Glaeser at al. (1992) and focused on changes in employment levels over time as measure of manufacturing growth. Here we take advantage of richer data to include not only employment but also total output, investment, and changes in the number of firms.

At the heart of most analyses of sectoral dynamics is the idea that a variable of interest y_{it}– typically the level of economic activity in a given country or location i–tends towards a steady state y_i^*. If we linearize the law of motion of y around its steady state or mean, we obtain a linear difference equation:

$$\Delta y_{it} = \rho(y_i^* - y_{it}). \tag{1}$$

Equation (1) implies that growth Δy_{it} is faster the further away y_{it} is from y^*. This is common sense: if y_{it} is converging towards y^*, it must eventually slow down as it reaches y^*. Parameter ρ expresses the speed with which y_{it} converges to its steady state: if $\rho = 1$, convergence is instantaneous; if ρ is small but positive, convergence is slow; if $\rho < 0$, y_{it} does not move towards y_i^* but in fact moves away from it.

Following Quah (1993) and Desmet and Fafchamps (2006), it is straightforward to extend the above model to allow for stochastic shocks v_{it}, in which case we have:

$$\Delta y_{it} = \rho(y_i^* - y_{it}) + v_{it}. \tag{2}$$

In this context, y_i^* can be thought of as y_{it}'s conditional mean and ρ as the speed at which y_{it} reverts to its mean[1].

In equation (2), it is common to assume that y_i^* depends on specific conditions z_i prevailing in location i, i.e., to posit that $y_i^* = f(z_i)$. We then write:

$$\Delta y_{it} = \rho(f(z_i) - y_{it}) + v_{it}. \tag{3}$$

1. Of course, if all countries or locations begin well below their conditional mean, most will be seen to revert to their mean from below, that is, most will grow, as in Mankiw, Romer and Weil (1991).

In general, researchers are interested not so much in growth itself but in $f(z_i)$ because it is indicative of the long run behavior of y_{it}. By linking the two, equation (3) enables researchers to infer something about $f(z_i)$ from the speed of growth: conditioning on y_{it}, equation (3) predicts that variables z_i that yield a higher steady state y_i^* also increase the growth rate Δy_{it}. This yields a testing strategy: regress growth Δy_{it} on initial condition y_{it} and a set of variables z_i thought to affect steady state y_i^*; if they are seen to speed growth, they should also raise y_i^*, and vice versa. The same reasoning can be extended to time-varying factors z_{it}. In this case, y_{it} can be thought of as following a moving target. As the target moves further away, y_{it} must speed up in order to catch up with it.

The above ideas form the basis of our testing strategy: if variables measuring agglomeration effects speed up growth, this is seen as evidence that they generate positive feedbacks raising y_i^*[2]. To illustrate how this works, let Q_{ijt} be total manufacturing output in location i and sector j at time t. By definition we have $Q_{ijt} = \sum_{k \in I_{ijt}} Q_k$ where k is an individual firm index and I_{ijt} is the set of firms present in location i and sector j at time t. We wish to know whether Q_{ijt} converges to a steady state or conditional mean that is affected by agglomeration effects. Our core regression is of the form:

$$\log \frac{Q_{ijt+1}}{Q_{ijt}} = \alpha_{ij} + \beta A_{ijt} + \gamma P_{ijt} - \rho \log Q_{ijt} + \tau_{jt} + u_{ijt} \tag{4}$$

where α_{ij} is a location-sector fixed effect, A_{ijt} is a vector of agglomeration variables, P_{ijt} is a set of direct productivity and cost measures, τ_{jt} is a sector-specific time dummy, and u_{ijt} is a residual. In our earlier notation, $y_{it} = \log Q_{ijt}$, $\rho f(z_{it}) = \alpha_{ij} + \beta A_{ijt} + \gamma P_{ijt}$, and $\tau_{jt} + u_{ijt} = v_{it}$. Location and sector specific fixed effects α_{ij} control for all time-invariant factors such as geographical location, proximity to borders, etc. Sector-specific time dummies τ_{jt} control for all shocks that are common across sectors in the economy, such as changes in interest rate or exchange rate. They also control for technological change in each sector. Agglomeration effects are thus identified by variations in A_{ijt} and P_{ijt} over time, relative to their national average. This ensures that we do not erroneously attribute to agglomeration effects what is in fact due to unobserved heterogeneity across locations.

For estimation purposes, it is customary to rewrite equation (4) in the form of a dynamic panel regression:

$$\log Q_{ijt+1} = \alpha_{ij} + (1-\rho) \log Q_{ijt} + \beta A_{ijt} + \gamma P_{ijt} + \tau_{jt} + u_{ijt}. \tag{5}$$

In the transformed regression, the coefficient of Q_{ijt} represents the speed of adjustment: the smaller it is, the faster adjustment is. Given the presence of fixed effects α_{ij}, estimation of (5) by OLS is known to generate inconsistent estimates. To deal with the difficulty, a number of alternative instrumental variable and GMM

2. This approach is but one way of studying agglomeration effects. Fafchamps and El Hamine (2017), for instance, examine the effect of agglomeration forces directly on firm productivity and wages.

estimators have been proposed in the literature[3]. Differencing the data to eliminate $□_{ij}$, (5) can be written:

$$\Delta \log Q_{ijt+1} = (1-\rho)\Delta \log Q_{ijt} + \beta \Delta A_{ijt} + \gamma \Delta P_{ijt} + \Delta \tau_{jt} + \Delta u_{ijt}. \tag{6}$$

GMM estimators for (6) rely on lagged values of $\log Q_{ijt}$ to instrument $□ \log Q_{ijt}$ (e.g., Anderson and Hsiao, 1982; Arellano and Bond, 1991). This is, for instance, the approach adopted by Combes (2000) and Combes *et al.* (2004)[4].

We are also interested in the channel through which agglomeration effects influence output. We focus on three possible channels: capital investment, employment, and firm entry and exit. Manufacturing growth can occur through the expansion of existing firms or through an increase in the number of firms N_{ijt}. As Combes (2000) has shown, which of these two avenues dominates depends on demand elasticity and on the nature of competition. Given that agglomeration externalities are at least in part due to competition, we suspect that agglomeration variables may have a different effect on firm expansion than on firm entry. Let L_{ijt}, K_{ijt} and N_{ijt} denote total employment, capital stock, and number of firms in location i and sector j at time t, respectively. We begin by estimating a model of the form:

$$\Delta \log Q_{ijt+1} = (1-\rho)\Delta \log Q_{ijt} + \beta \Delta A_{ijt} + \gamma \Delta P_{ijt}$$
$$+\theta_l \Delta \log L_{ijt} + \theta_k \Delta \log K_{ijt} + \theta_n \Delta \log N_{ijt} + \Delta \tau_{jt} + \Delta u_{ijt}. \tag{7}$$

Comparing estimates of parameter vectors □ and □ between equations (6) and (7) should yield the first hints on whether agglomeration A_{ijt} and productivity P_{ijt} affect output growth directly or indirectly through investment, hiring, and firm entry: if agglomeration externalities affect output indirectly by fostering a change in employment, investment, or firm entry, estimated coefficients □ and □ in equation (7) should be smaller than in (6).

We also examine how employment growth, investment, and firm entry and exit respond to A_{ijt} and P_{ijt}. Our regressions are of the form:

$$\Delta \log X_{ijt+1} = \varphi_1^x \Delta \log L_{ijt} + \varphi_2^x \Delta \log K_{ijt} + \varphi_3^x \Delta \log N_{ijt} + \varphi_4^x \Delta A_{ijt}$$
$$+\varphi_5^x \Delta P_{ijt} + \Delta \tau_{jt}^x + \Delta u_{ijt}^x$$

where X stands for L, K, and N, respectively. Since L_{ijt}, K_{ijt} and N_{ijt} feed back into each other, they are to be regarded as pre-determined variables. Consequently, their first differences are all instrumented with lagged levels of L_{ijt}, K_{ijt} and N_{ijt}. We further refine this approach by decomposing net firm entry into sub-components. A net increase in N_{ijt} requires that gross entries N_{ijt}^e and firm in-migration N_{ijt}^n from

3. See for instance Arellano (2003) and Arellano and Honoré (2001) for summaries of the literature.

4. Combes *et al.* (2004) estimate a version of (5) where the dependent variable is L_{ijt} / N_{ijt}, i.e., employment per firm. Given that the model is estimated in logs and that N_{ijt} appears as regressor (see infra), their models is basically equivalent to ours in that respect.

other locations exceeds gross exit $N^x_{ijt-1} < 0$ and firm out-migration to other locations $N^o_{ijt-1} < 0$:

$$\Delta N_{ijt} = N^e_{ijt} + N^n_{ijt} + N^x_{ijt-1} + N^o_{ijt-1}$$

To investigate whether agglomeration externalities and productivity shocks affect entry, exit, and firm relocation differently, we also estimate models of the form:

$$\log(N^z_{ijt+1} + N_{ijt+1}) - \log N_{ijt} = \varphi^x_1 \Delta \log L_{ijt} + \varphi^x_2 \Delta \log K_{ijt} + \varphi^x_3 \Delta \log N_{ijt} + \varphi^x_4 \Delta A_{ijt} + \varphi^x_5 \Delta P_{ijt} + \Delta \tau^x_{jt} + \Delta u^x_{ijt} \qquad (8)$$

for $z = \{e, n, x, o\}$. This formulation offers the advantage that all estimated coefficients are expressed in terms of their effect on the growth rate of the number of firms. Since equation (8) does not include a lagged dependent variable, the GMM estimator of Arellano and Bond does not apply. We nevertheless worry that L_{ijt}, K_{ijt}, and N_{ijt} may be correlated with the fixed effect. For this reason $\Delta \log L_{ijt}$, $\Delta \log K_{ijt}$ and $\Delta \log N_{ijt}$ are nonetheless instrumented using lagged levels when estimating (8).

We now turn to a description of our regressors. We follow Fafchamps and El Hamine (2017) and identify four variables measuring agglomeration effects A_{ijt} [5]: (1) total manufacturing employment in location i at time t – $L_{it} = \sum_j L_{ijt}$; (2) the total number of manufacturing sectors M_{it} present in location i at time t; (3) a diversity index D^*_{it} defined as

$$D^*_{it} = \frac{1}{\sum_{j \in \Gamma_{it}} \left(\frac{L_{ijt}}{L_{it}} \right)^2}$$

where Γ_{it} is the set of sectors present in location i at time t; and (4) a competition index C^*_{ijt} defined as

$$C^*_{ijt} = \frac{1}{\sum_{k \in \Gamma_{ijt}} \left(\frac{L_k}{L_{ijt}} \right)^2}.$$

Both D^*_{it} and C^*_{ijt} are Herfindahl indices. Complete concentration in a single sector (D^*_{it}) or firm (C^*_{ijt}) yields a value of 1. In contrast, if employment is equally shared among sectors, the diversity index becomes:

$$D^*_{it} = \frac{1}{\sum_{j \in \Gamma_{it}} \left(\frac{L_{it} / M_{it}}{L_{it}} \right)^2} = \frac{1}{\sum_{j \in \Gamma_{it}} \left(\frac{1}{M_{it}} \right)^2} = M_{it}.$$

5. Combes *et al.* (2004) also regard L_{ijt} and N_{ijt} as capturing agglomeration effects. We are not comfortable with this interpretation (see below).

By the same token, when all firms are of equal size, $C^*_{ijt} = N_{ijt}$. To facilitate interpretation, we normalize D^*_{it} and C^*_{ijt} as follows:

$$D_{it} = \frac{D^*_{it}}{M_{it}},$$

$$C_{ijt} = \frac{C^*_{ijt}}{N_{ijt}}.$$

Normalized indices vary between 0 (most concentrated) and 1 (least concentrated).

Several of the above variables have been used in one form or another in the literature before, typically in log form. For instance, own sector employment $\log L_{ijt}$ is referred to by Henderson (2003) as a localization effect while $\log L_{ijt}$ is said to capture urbanization effects. Sometimes similar variables are given a different interpretation. Henderson (2003), for instance, uses N_{ijt} as the number of sources of local information spillover while Combes *et al.* (2004) regard N_{ijt} alone as a measure of competition. In the work of Glaeser *et al.* (1992), it is the (log of the) ratio N_{ijt} / L_{ijt} that is used as a measure of competition. The likely reason for these discrepancies is differences in data availability: authors with different types of data end up using different sets of agglomeration variables.

We are not comfortable interpreting the coefficient of $\log L_{ijt}$ as measure of agglomeration effects. The reason is that firms would typically grow even in the absence of agglomeration externalities. Summing over all firms would generate a relationship between $\Delta \log L_{ijt}$ and $\log L_{ijt}$ even though agglomeration effects are absent. The same reasoning also applies to firm entry and exit: firms would enter and exit even in the absence of agglomeration effects. To identify the agglomeration effect of L_{ijt} and N_{ijt}, firm-level data is required as to distinguish between factors that are internal and external to individual firms.

The meaning of each variable depends on the presence or absence of the others: variables can only be interpreted in conjunction with each other. Assuming that all variables enter in logs, L_{ijt} captures the agglomeration effect due to the presence of a large manufacturing sector. The effect of specialization L_{ijt} / L_{it} is captured in the coefficient of L_{ijt}, together with growth factors that are internal to firms. Competition is captured by C_{ijt} which, after normalization, can be interpreted independently from N_{ijt}. If competition generates positive agglomeration externalities, as suggested by Porter, then C_{ijt} should have a positive effect on productivity and hence on firm growth.

Diversity is captured by two variables, M_{it} and D_{it}. Since we are conditioning on sectoral specialization through L_{ijt} / L_{it}, the variables M_{it} and D_{it} measure the effect of diversity in sectors other than *j*. For a given level of specialization, firm performance may increase with the diversity of production in sectors other than the firm's own sector *j*. It is this effect that variables M_{it} and D_{it} seek to capture. If diversity in other sectors is good for manufacturing firms, then we expect both M_{it}

and D_{it} to have a positive effect on firm performance. Comparison of their effects can tell us whether it is the mere presence of a sector that matters or whether it is the equal distribution of employment across sectors.

As we pointed out earlier, agglomeration variables A_{ijt} are meant to proxy for productivity effects due to location externalities (e.g., Glaeser *et al.*, 1992; Henderson, 1997; Combes, 2000; Combes *et al.*, 2004; Bun and Makhloufi, 2007). In the context of this literature, productivity should be understood in a broad sense: it encompasses the effect that Marshallian and pecuniary externalities can have on the joint productivity of all firms in a given location. Marshallian externalities raise total factor productivity directly while pecuniary externalities raise output prices and/or lower wage and intermediate input costs. Fafchamps and El Hamine (2017) have shown that both total factor productivity and wages are strongly influenced by agglomeration effects. Consequently, we let the P_{ijt} vector include measures of total factor productivity as well as factor costs.

We estimate all models with and without P_{ijt} variables. Intuitively, if agglomeration variables capture productivity effects, then the inclusion of direct productivity measures P_{ijt} should set the coefficients of agglomeration variables to 0. The validity of this test rests on the assumption that P_{ijt} is measured without error. If measurement error is present, we would expect some of the productivity effects to be capture by A_{ijt} variables, in which case their coefficient may remain significantly different from 0. But even in this case, we expect □ to fall in absolute value.

Before turning to the empirical analysis, we need to recognize its logic and limitations. First, our focus is on local snowballing effects, i.e., we ask whether location-specific variation in productivity or agglomeration variables has a delayed effect that ripples through all sectors in that location. Since we control for location–sector fixed effects and focus on year-to-year variation, long-lasting agglomeration effects are not picked up by our approach. Similarly, since we control for sector-year fixed effects, our approach nets out any time-varying sector-specific effect that operates at the level of the country. We also do not consider ripple effects on neighboring locations. Identification of agglomeration effects is achieved solely from observing yearly variation within each sector and location.

Second, our analysis encompasses all locations where manufacturing firms are found, including locations with very few of them. In other words, we do not limit our analysis to large metropolitan areas. Small localities are worthy of attention because, if anything, agglomeration effects should be comparatively larger there: a local productivity shock is more likely to snowball to other firms if agglomeration externalities in manufacturing are an important contributor to town formation. The data also include many small firms, a feature that may affect our results regarding entry and exit. The role of the rapid growth of new entrants in the creation major industrial hubs–e.g., the Silicon Valley–has caught the attention of many. We want to see whether insights generated by such experiences translate to small manufacturers in a middle-income country such as Morocco.

Third, nothing in our analysis enables us to distinguish between pure externalities and general equilibrium effects that are location specific. While the concept of Marshallian or technological externality is well defined in our context–it raises or lowers total factor productivity–the concept of pecuniary externality is not clearly distinguished from other general equilibrium effects[6]. Ultimately, it is a matter of semantics whether we want to call agglomeration effects an externality or not. With this caveat in mind, we now turn to the data.

2. The Data

To implement the above testing strategy, we use manufacturing census data from Morocco. The data were collected by the Moroccan Ministry of Commerce and Industry every year over the period 1985 to 2001. Coverage is universal and includes all manufacturing enterprises in all sectors and all parts of the country. Given that answering the annual census questionnaire is a legal obligation, the rate of non-answer is fairly small – 12% over the entire period[7]. These data have already been studied by others. The first years of this data set have been used by Clerides, Lach and Tybout (1998) to examine export behavior. The relationship between exports and productivity is also studied by Fafchamp *et al.* (2008). Fafchamps and El Hamine (2017) test the effect of agglomeration externalities on total factor productivity and wages. Fafchamps and Schündeln (2013) show that local bank availability is associated with faster growth for small and medium-size firms in sectors with growth opportunities, with a lower likelihood of firm exit and a higher likelihood of investment.

The sectoral decomposition identifies 17 different sectors corresponding roughly to the 2-digit ISIC classification. Because 3 of the sectors have very few firms, for the sake of the analysis we combine them with other similar sectors, bringing the total number of sectors to 14. Data is available for all years on output, employment, wage payments, investment, and disbursed capital (a balance sheet equity concept). Capital stock information is available for the year 2001. Employment figures are separated into permanent and casual workers, the latter figure being given in total number of days per year. We divide the number of man-days by 256 to transform man-days of casual labor into permanent employee equivalent[8]. To facilitate

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6. In the theoretical literature, the term pecuniary externality is sometimes used to describe situations in which market interactions generate multiple Pareto ranked equilibria (e.g., Murphy, Shleifer and Vishny, 1989; Ciccone and Matsuyama, 1996). Elsewhere (e.g., Romer, 1986; Rodriguez-Clare, 1996, Fafchamps, 1997), pecuniary externalities describe multiplier effects. Our empirical analysis can neither identify multiple equilibria nor distinguish multiplier effects that arise from normal general equilibrium feedbacks from those that arise from pecuniary externalities.

7. For the purpose of generating national and regional statistics, the Ministry of Commerce and Industry imputed values individually for each non-responding firm. Imputation was typically done using previous year information. Imputed firms are ignored in the regression analysis but to minimize measurement error imputed employment figures for non-respondent firms are used in computing the agglomeration variables described in the previous section.

8. This corresponds to 365–52 x 2 (week-ends)–6 (public holidays).

comparison, we deflate all output figures using sector-specific GDP price deflator. Investment data is deflated using the price index for machinery[9].

Location information varies over time. From 1985 until 1993, the manufacturing census only recorded the province in which the firm was located. This period correspond to a trade liberalization phase (Haddad and de Melo, 1996). From 1994 until 1997, the data also recorded the city code and from 1998 on the precise commune location of each firm was recorded. Morocco is divided into 70 provinces, 67 of which count at least one manufacturing firm over the study period. Starting from 1993, the data distinguishes between 242 cities. From 1998, firm location data is available at the commune level. There are approximately 1300 communes in Morocco, 689 of which had at least one manufacturing firm over the study period.

These data are used to construct three sets of location and sector specific variables: at the commune, city, and province level. Commune and city aggregates can be computed from 1998 until 2001 and from 1994 until 2001, respectively. Province aggregates can be computed for the whole span of the data, that is, from 1985 until 2001. Summary statistics are presented in Table 2. The table is organized a way that mirrors the subsequent analysis: each observation corresponds to a sector, location, and year with at least one active firm. Locations with no manufacturing are omitted form the table – they provide no information about agglomeration effects. The three panels correspond to the varying level of geographical detail available in the census data.

Average sectoral employment at the commune level is around 360 workers. The median is much lower at 53. Total manufacturing employment in the commune is a little over 4000 on average. There are on average around 5 firms in each sector and commune, with a smaller median of 2. The corresponding value of the (unnormalized) competition index C^*_{ijt} is 2.7, hence falling roughly between 1, which corresponds to complete concentration, and N_{ijt} which correspond to complete equality conditional on N_{ijt}. Around 8 of the 14 sectors are present in a commune on average. The average (unnormalized) diversity index D^*_{it} is 3.3, which similarly falls between 1 and M_{it}. Entry, exit, and movement across locations are presented next. We see that the number of entering and exiting firms are roughly of the same order of magnitude. This is consistent with the relative stagnation of Moroccan manufacturing in the late 1990's. The exit rate is high: in any given year 10% of all firms exit. This reflects the small nature of many of the firms in the manufacturing census. Small firms are indeed known to have a higher churning rate (e.g., Daniels, 1994; Barrett, 1997). We also see that many firms move across locations. By the nature of the data, no information on firms exiting or moving out is available for the last year, hence the smaller number of observations. As suggested by the large difference between the mean and the median, investment I_{ijt} is highly skewed. This is normal given the predominance of small firms in the sample (e.g., Bigsten *et al.*, 2004).

9. Since we include sector-specific year dummies in all regressions, deflating is not really an issue. But it matters for back-predicted capital stock, as explained below.

The second and third panels show similar statistics when geographical location is defined at the level of the city and province, respectively. While there are on average 18.5 communes per province, the number of communes with manufacturing employment is only 2.9 times the number of provinces. This suggests that, within each province, manufacturing employment is geographically concentrated in a few communes. Comparison between the three panels indicates that values are roughly multiplied by 2.5-3 between the commune and province data. Because of this – and the used of lagged variations – there is much larger number of usable years when using province instead of commune data, in spite of the reduction in the number of locations.

3. Productivity and wages

Before we turn to the estimation of our model of interest, we need to generate the productivity variables. Ideally, we would like to have information on total factor productivity in volume, plus data on output prices, wages, and input costs – since theoretically they can all channel externalities. In practice, we do not have information on output prices and input costs. Consequently, we focus our attention on wages and total factor productivity in value.

Wage w_{ijt} is obtained by dividing, for each firm, the total annual wage bill by the number of employees[10]. We then take the median of the location and sector as our wage measure w_{ijt}. The median is preferred to the mean because it is less sensitive to measurement error[11].

To obtain an estimate of total factor productivity in value, we estimate, for each firm k in our sample, a Cobb-Douglas production function of the form:

$$\log Q_{kt} = \theta_0 + \theta_1 \log L_{kt} + +\theta_2 \frac{L_{kt}^{casual}}{L_{kt}} + \theta_3 \log K_{kt} + \theta_4 Z_{kt} + e_{kt} \tag{9}$$

where Q_{kt} is the value of output, L_{kt}^{casual} is the number of casual workers (in permanent employee equivalent units), and Z_{kt} is a vector of control variables including the log of the firm's age, the squared log of age, the share of foreign and government ownership, dummies for limited liability and corporate status, as well as sector, region, and year dummies. Since capital stock information is only available for 2001, we fit a predictive equation to the 2001 data and use the estimated coefficients to predict the capital in other years[12].

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10. Casual workers are measured in permanent employee equivalent units.

11. Since w_{ijt} is obtained by dividing two variables reported with error, its distribution has fat tails driven by very large and very small outliers. Using the median takes care of this problem. In practice, using the average wage instead of the median does not change results much.

12. The predictive regression is presented in appendix and discussed in detail by Fafchamps and El Hamine (2017). A small number of firm characteristics such as age, legal status, foreign or public ownership, as well as sectoral and location dummies are included as regressors. Time varying predictors include lagged labor and share of casual workers, investment and lagged investment, dummies for whether the firm invested in the current and previous period, and a dummy for whether is in its first year of existence, in which case all lagged values are set to zero. This parsimonious model explains two thirds of the variation in capital stock across firms in 2001.

Predicted values of capital $\hat{K}_{kt}$ are then used in lieu of capital in equation (9) as well as in subsequent analysis. This implies that capital is de facto instrumented. To avoid simultaneity bias, the two labor variables are also instrumented using the same variables used to predict capital, namely, lagged labor, firm equity, a dummy if the firm existed in the previous year, and variables measuring lagged investment. All values are deflated using sector-specific deflators. Results are presented in Table 2. The show that this simple, parsimonious model accounts for more than three fourth of the variation in firm output. Labor and capital share parameters take reasonable values.

The residuals $\hat{e}_{kt}$ from equation (9) are then obtained. The median residual $\hat{e}_{kt}$ for a given sector, year, and location is our measure of firm total factor productivity p_{ijt}. Together, w_{ijt} and p_{ijt} form the p_{ijt} vector. The reader should keep in mind that since we cannot construct an input price variable, we cannot control for possible productivity effects that take place via intermediate inputs or service costs.

4. Dynamic Panel Analysis

We now turn to the dynamic panel analysis. We begin with the output growth equation (6). All regressors are in logs[13].

Results for equation (6) are reported in Table 3 using the GMM estimator proposed by Arellano and Bond (1991)[14]. Robust standard errors are used throughout. Since we do not know at what geographical level agglomeration effects are felt, three sets of two regressions are reported, each set corresponding to a different geographical unit of analysis. The first two columns refer to the commune data, which only runs from 1998 until 2001. The second set of two columns refers to the city data which runs from 1994 until 2001, and the last set refers to provinces, with data from 1985 until 2001. For each of these sets, two regressions are estimated: without and with productivity variables p_{ijt} and w_{ijt}. The number of observations increases as one moves from commune to city to province data, reflecting the increase in the number of usable years of data. At the bottom of this Table – and subsequent Tables – we report autocorrelation tests on the residuals[15]. We also

13. Productivity shocks $\hat{e}_{kt}$ are by construction expressed in logs.

14. Following the recommendation of Arellano and Bond (1991), we report one-step GMM estimates throughout because two-step estimates are known to seriously underestimate standard errors in finite samples. This is confirmed in our case: two-step estimates are very similar to one-step estimates, but *t* values are unrealistically large. To check for robustness, we also estimate equation (6) using the slightly less efficient instrumental variable method suggested by Anderson and Hsiao (1982). All pre-determined differenced regressors are instrumented using lagged levels. Results are very similar to those obtained with GMM. Even with robust standard errors, inference is virtually identical.

15. The Arellano and Bond estimator is known to be consistent under first order autocorrelation, but not under second order autocorrelation. A Sargan overidentification test was also conducted. When calculated under the assumption of homoscedastic errors, the Sargan test is known to over-reject the null in the presence of heteroscedasticity in this category of models. Sargan tests based on the two-step model, which corrects for heteroscedasticity, all fail to reject overidentification.

report a joint test of the agglomeration variables A_{ijt} and productivity variables P_{ijt}. Since we control for fixed effects, all reported coefficients are purged of time-invariant location and sector-specific effects, such as those that could be due to pure geographical advantages.

Results are broadly similar across the three sets of regressions: inference does not appear to depend on the geographical unit of analysis. This is probably due to the fact that communes with manufacturing activity tend to be located close to each other within each city and province. We find a large and positive coefficient on lagged output Q_{ijt}, indicating a lot of persistence in economic activity. Total employment in location L_{it} has a strong negative effect in all three regressions, suggesting that the presence of manufacturing employment has a negative effect on manufacturing growth. This is consistent with the existence of negative agglomeration externalities due to congestion. The competition index C_{ijt} is positive and significant in all three regressions: less concentration within a sector is beneficial to growth in this sector. The number of manufacturing sectors present in a location has a positive effect on manufacturing output growth, but the effect is only significant in the first regression. In contrast, the diversity index D_{it} is everywhere negative, significantly so in the city and province regressions. Taken together, these results appear to reject Jacobs' idea that manufacturing diversity is beneficial to growth: locations with less diversified manufacturing on average grow faster.

Adding the two productivity variables to the regression does not, contrary to expectations, reduce the effect of agglomeration variables L_{it}, M_{it}, C_{ijt} and D_{it}; in most cases it even magnifies their coefficient, as evidenced by higher individual *t*-values and a higher Wald test statistic for joint significance (see bottom of Table 3). This flies in the face of the idea that agglomeration effects on growth operate through productivity. Variable p_{ijt} also behave in an unexpected manner: contrary to expectations, it has a strong negative coefficient in all three sets of regressions. This means that, controlling for time-invariant sector and location effects, a rise in productivity at time t is associated with slower growth of output at time $t + 1$. This result contradicts the idea that productivity gains are what fuels manufacturing growth at the local level. In contrast, the wage variable has the anticipated negative sign: a rise in local manufacturing wages at t leads to slower output growth at $t + 1$, possibly because firms leave the location for another one with lower labor costs. We revisit this hypothesis below.

One likely explanation for the negative sign on p_{ijt} is that productivity in value is subject to non-persistent shocks: as productivity reverts towards its mean after a large positive shock, output tends to fall. This interpretation finds some support in the results: once we control for past productivity, the coefficient on lagged output rises above one in all three regressions. This means that if output rises at t for reasons other than a productivity shock (e.g., because of investment or firm entry), this rise leads to an even faster increase in output in subsequent periods. In contrast, if output rises at t because of a productivity shock, it tends to fall subsequently, suggesting that the productivity shock was short-lived. No matter what the underlying mechanism, this findings flies in the face of the idea that productivity shocks snowball through the economy, generating positive feedbacks between firms and triggering a virtuous growth cycle. This is not what we observe in Moroccan manufacturing.

To investigate this further, we estimate equation (7) which include L_{ijt}, N_{ijt} and K_{ijt} as additional regressors. As indicated earlier, these variables are regarded as pre-determined in the estimation, and thus their differences are instrumented with lagged levels. Regression results are presented in Table 4. Inference regarding agglomeration and productivity variables is basically unchanged by the presence of L_{ijt}, N_{ijt} and K_{ijt}: whatever agglomeration and productivity variables are measuring, it is not past firm expansion. As anticipated, the introduction of the new regressors brings down the coefficient of lagged output below 1. But estimated coefficients for L_{ijt}, N_{ijt} and K_{ijt} are highly variable–switching sign and significance from one regression to the other. Results for employment and number of firms are by and large inconclusive, probably because multicollinearity with lagged levels of output and capital precludes reliable identification. Results are slightly more stable for capital: once we control for past productivity shocks, investment at t is associated with a *fall* in output at $t + 1$. We revisit this puzzling result below.

To investigate issues more in detail, we turn to the effect that agglomeration and productivity variables may have directly on investment, employment growth, and firm entry and exit. We begin with employment growth, which has been the primary focus of much of the literature to date. Results are presented in Table 5, again using the Arellano and Bond GMM estimator. Other estimation details are the same as in Table 4[16].

We again find evidence of a lot of persistence, with coefficients on lagged employment fluctuating between 0.68 and 1.05, depending on the regression. An increase in the number of firms at t is associated with employment growth at $t + 1$. This is consistent with the idea that new firms go through an initial period of rapid growth as they converge to their firm-specific steady state. Surprisingly, passed changes in capital stock are not reflected in subsequent employment growth. To verify whether this result is due to the fact that we are using predicted capital in lieu of actual capital stock, we reestimate the model using the simpler Anderson and Hsiao approach. This enables us to used lagged investment instead of change in predicted capital stock[17]. Results, not shown here to save space, are identical: it is not the reliance on predicted capital stock that accounts for the non-significant coefficient on capital.

The effect of agglomeration variables on the growth of sectoral employment is by and large identical to their effect on output: total employment L_{it} and diversity

16. In particular, L_{ijt}, K_{ijt} and N_{ijt} are regarded throughout as pre-determined variables and instrumented using lagged levels. Robust standard errors are reported throughout.

17. Because capital is pre-determined, however, investment at t must instrumented with lagged levels of predicted capital.

D_{it} have strong negative effects, while the competition index C_{ijt} is strongly positive. Within-sector competition thus appears beneficial to employment growth while total manufacturing employment and sectoral diversity have negative effects. The number of sectors M_{it} appears with a significantly positive coefficient in the commune data, but the effect disappears as we move to the province data. This suggests that the effect of M_{it} may have changed over time or depends strongly on the size of the geographical unit.

Productivity variables p_{ijt} and w_{ijt}, in contrast, behave in a completely different way compared to their effect on output: both variables have positive effects in the commune, city and province regressions. The level of significance of the productivity variable remains low, however. What these results imply is that a rise in productivity or wages at time t leads to a subsequent rise in employment at $t + 1$. For productivity, this effect is what theory predicts: as productivity increases, firms hire more workers. But the effect of w_{ijt} is contrary to theory: manufacturing employment is seen to increase *after* a rise in manufacturing wages.

Turning to investment, we again find evidence of persistence (see Table 6). But the coefficient of lagged capital is much lower than that of labor – between 0.37 and 0.58 compared to 0.68 to 1.05. This is consistent with the observation that, in poor countries, investment is sporadic, perhaps due to convexity in adjustment costs (e.g., Bigsten *et al.*, 2004). In further contrast with Table 5, we find that lagged employment growth has a strong effect on investment: locations and sectors that have expanded employment in the past tend to experience more investment in the future. Put differently, employment growth tends to lead investment instead of the contrary, as is often assumed. This again is consistent with the existence of convex adjustment costs or option effects: firms increase employment before investing (e.g., Dixit, 1989: Dixit and Pindyck, 1994).

Agglomeration variables have by and large the same effect on investment as they have on employment, so we need not discuss them again. But p_{ijt} and w_{ijt} behave in a different manner. Here we find a strong and robust association between past productivity increases and investment: locations and sectors that experienced a large increase in productivity at t are more likely to invest at $t + 1$. Since positive productivity shocks are associated with a subsequent fall in output, this suggests that firms may be behaving in a myopic manner, failing to see that the current productivity shock is short-lived. An alternative explanation is that firms are credit constrained. By raising current revenues, a favorable productivity shock enables firms to undertake investment that they could not previously undertake (e.g., Fazzari, Hubbard and Petersen, 1988; Hubbard, 1998; Bigsten *et al.*, 1999; Fafchamps and Oostendorp, 2002; Nkurunziza, 2010; Fafchamps and Schündeln, 2013).

Table 7 shows a similar regression analysis for the number of firms N_{ijt}. Results suggest a very high level of persistence for firm numbers: the coefficient on lagged N_{ijt} oscillates between 0.89 and 1.5. Lagged employment and capital are only significant in the province regression, labor with a positive coefficient and capital with a negative one. Put differently, employment growth at t is associated with net firm entry at $t + 1$ while investment at t seems to lead to firm exit. The first effect suggests that when existing firms expand employment, new firms enter. Alternatively, when existing firms cut down their workforce, displaced workers seek self-employment through the creation of small firms. The second effect may be due to the fact that investment by existing firms displaces smaller firms, hence leading to firm exit– e.g., if self-employed workers close their firm to join the workforce of larger firms. While agglomeration variables again have the same effect on net firm entry, p_{ijt} and w_{ijt} are non-significant, except for wages which appears with a positive and significant coefficient in the province regression.

We further investigate firm entry by decomposing $\Delta \log N_{ijt}$ into gross entry, firm in-migration, firm out-migration, and gross exit and estimating equation (8). As explained in Section 2, the GMM estimator of Arellano and Bond does not strictly apply. The model is therefore estimate using the Anderson and Hsiao approach of instrumenting first differences with lagged levels. Results are summarized in Table 8. Robust standard errors and a 10% significance level are used for inference purposes. Since exit and out-migration appear as negative variables, the signs of all coefficient is immediately comparable.

We find that persistence affects all four dependent variables: a larger number of firms increases entry and in-migration and reduces exit and out-migration. The positive effect of employment on N_{ijt} that is significant in the province regression appears to take place through increased gross entry and reduced out-migration; exit and in-migration are not affected. The negative effect of investment on N_{ijt} in the province regression appears driven primarily by increased firm exit. Agglomeration variables affect our four dependent variables differently. Total employment L_{it} depresses N_{ijt} via its effect on entry, exit, and out-migration. In contrast, firm in-migration does not appear to be affected by changes in L_{it} over time. The number of sectors, which is non-significant in Table 7, tends to be non-significant here as well, except for a few regressions where the effect in significantly negative. Much of the negative effect of diversity on N_{ijt} appears to be due to reduced gross entry. Diversity also tends to reduce out-migration and firm exit, but the effect is only significant in the commune regression.

Competition has a positive and significant effect in most regressions: less concentration reduces firm exit and out-migration while encouraging more entry and in-migration. According to the literature (e.g., Nelson and Winter, 1982; Clerides *et al.*, 1998; Das, Roberts and Tybout, 2001; Haddad and Norton, 2001), the effect of competition on productivity is thought to come from the elimination of inefficient firms and entry by newer, more productive firms. In this case, we would expect that increased competition increases both entry *and* exit. This is not what we find.

Finally, p_{ijt} is seen to have a negative effect on firm in-migration and a positive effect on exit in the city regressions. The wage variable w_{ijt}, in contrast, tends to raise entry and reduce exit in the province regression. Neither results are consistent with the agglomeration externality idea that locations with favorable productivity shocks attract new firms, or that higher wages drive firms away.

Conclusion

The literature has attempted to provide evidence of agglomeration externalities by regressing sectoral employment growth on variables meant to capture location-specific specialization, competition, and diversity (e.g., Glaeser *et al.*, 1992; Henderson, 1997; Combes, 2000; Combes *et al.*, 2004; Bun and Makhloufi, 2007). Evidence of an influence of agglomeration variables on growth has generally been taken as evidence of productivity effects. In this paper, we have tested the validity of this approach in two ways: by controlling directly for productivity, and by comparing results obtained using employment growth with those using output, investment, and firm entry and exit. What makes these improvements possible is detailed and exhaustive firm-level data available over an extended period of time. In our econometric analysis, we control for location and sector specific fixed effects and correct for the fact that some regressors are pre-determined.

We find strong and robust evidence of agglomeration effects. Moreover, none of our results depends on the level of geographical disaggregation: we obtain similar findings whether working with commune, city, or province data. This is hardly surprising given that, within provinces, manufacturing remains concentrated in a few nearby locations. Our results show that a rise in total manufacturing employment in a locality predicts a negative growth in output, employment, capital, and number of firms in the following year. We also find that sectoral concentration is inimical to growth: locations and sectors where firms are of equal size tend to grow faster in terms of output, employment, and capital. Firm entry is also higher. Finally, locations with equal distribution of employment across various manufacturing sectors grow significantly slower, again in terms of output, employment, capital, and number of firms. If we interpret these results as other authors have done, we would conclude that competition is good for growth–and diversity bad–because of their effect on productivity.

Other findings, however, cast some doubt on this interpretation. First, agglomeration variables have an effect on local sectoral growth that is virtually opposite to the one they have on individual firm productivity. Indeed, using the same data set Fafchamps and El Hamine (2017) estimate the effect of agglomeration variables on wages and total factor productivity at the individual firm level. They find that competition reduces productivity while diversity raises it – the opposite result from what we find here.

Second, if agglomeration variables influence manufacturing growth through their effect on productivity, controlling for productivity directly should eliminate or, at the very least, reduce the significance of agglomeration variables. In our detailed analysis, we find instead that none of the agglomeration effects is seriously affected when we introduce measures of total factor productivity: in none of our regressions do productivity variables lower the significance of agglomeration variables. Agglomeration variables capture something that is relevant to firm growth, but it is not total factor productivity in value.

To be fair, our productivity variables do not always behave as anticipated either. In particular, past productivity shocks tend to lower future output growth. We interpret this finding as consistent with the idea that productivity shocks are not very persistent; reversion to the mean implies slower future growth. We also find that a rise in productivity raises subsequent employment and investment, but has no effect on firm entry and exit. The effect is particularly strong on investment, suggesting that firms invest more in the wake of a positive productivity shock when revenues are high, possibly because they are liquidity constrained (e.g., Hubbard, 1998; Bigsten *et al.*, 1999; Bigsten *et al.*, 2003).

The analysis presented here raises many new questions. The literature has relied on certain variables thought to affect productivity in order to measure agglomeration externalities. Our findings suggest that this approach is unreliable, at least in the context of Morocco: 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 are strong and robust predictors of manufacturing growth. What is unclear is why. But we can speculate.

First, over the study period, Moroccan manufacturing is a relatively small sector of the economy heavily concentrated in three sectors – garment, textiles, and leather products – that account for 80% of all manufacturing employment and are heavily exported (e.g., Fafchamps, El Hamine and Zeufack, 2008; Fafchamps, 2009). The Moroccan textile and garment value chain is extremely short, with heavy reliance on cut-and-trim[18] sub-contracting for European buyers, predominantly in France and Spain. Production orders are short–a few days–and the manpower is largely composed of female casual workers. The three sectors are subject to large demand swings driven by shocks in foreign demand and competitivity with Chinese exports. This means that vertical linkages within the manufacturing sector are minimal and production is heavily dependent on conditions abroad. This leaves less room for agglomeration effects operating through industrial linkages and pecuniary externalities through local demand. Since firms compete for the same export orders, productivity shocks– i.e., above average sales–do not diffuse across firms. This may explain why we do not find evidence of agglomeration effect through productivity diffusion.

Secondly, manufacturing in Morocco is characterized by the coexistence of medium to large scale modern firms, with small survivalist enterprises created primarily to make ends meet. This is associated with wide disparities in the productivity level and management practices of firms (Bloom and van Reenen, 2007). When medium to large firms shed workers, small firms pick up the slack until jobs

18. In cut-and-trim, the buyer supplies all the designs and raw materials (e.g., fabric, buttons). This is related to the fact that Moroccan garment manufacturing partly serves the role of stop-gap supplier for large French and Spanish department stores: when they stock-out on a mass-produced garment in China and they wish to restock their inventories at short notice, they subcontract Moroccan manufacturers on a cut-and-trim basis. This singularly reduces opportunities for vertical linkages.

in medium to large firms are restored. We believe this pendulum process explains some of the findings regarding the entry and exit of firms in response to productivity shocks and agglomeration effects.

Third, we have looked for evidence of agglomeration effects at a fairly disaggregated geographical level. As a result, the sample used for estimation counts a lot of small localities, many of which are dominated by small informal firms. This means that our findings are heavily influenced by what happens to small firms. Because they have very different management practices from large firms, we also suspect that informal sector firms may not benefit from the same agglomeration externalities as those that benefit modern firms. In particular, small firms would not be able to absorb innovations in technology and management that spread through modern firms. This may explain why, in our data, past productivity improvements do not predict future growth in sales.

While these features may explain why our findings differ from what has been found in more advanced economies with large modern manufacturing, it does not imply that they are uninteresting. Quite the contrary. To date the literature has approached agglomeration externalities in a fairly monolithic way, as if they applied equally in all economies. Given what we now know of the lower tail of the firm productivity distribution in developing countries (Bloom and van Reenen, 2007), it is not too surprising that they do not benefit from agglomeration through the diffusion of productivity shocks. More likely, they conglomerate where local demand is, creating congestion and strong competition among them, and this what we pick up in our results.

To conclude, we have found agglomeration effects in Moroccan manufacturing but have found no evidence that they are due to productivity spillovers across firms. When we consider the nature of manufacturing in the country at that time, this may not been so surprising after all. If so, we need to reconsider the nature of agglomeration externalities in the developing world, and especially in Africa. Urbanization has spawned a myriad of small firms there, and our dominant models of industrial development appear in need of a rethink before we can successfully apply them to these new towns and cities.

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