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The Micro-Origins of Business Cycles: Evidence from German Metropolitan Areas

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Abstract

How large is volatility due to large firms? We answer this question through both reduced-form analysis and a calibration exercise. First, we exploit time and spatial variation across German cities and show that i) higher concentration is associated with more persistent local business cycles, ii) local concentration Granger-causes local employment volatility. From a business cycle perspective, we find evidence in favor of granularity-driven recessions only. Next, we calibrate a structural model along the lines of Carvalho and Grassi (2019) and find that the more fat-tailed productivity distribution in bigger cities crucially depends also on the higher probability for firms to grow.

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1 Introduction

When Amazon.com Inc. announced the decision to open a second headquarter in 2017 and hire additional 50.000 workers, 238 U.S. cities signed up to become home to the second most valuable U.S. company, attracted by the employment gain and the potential positive spillovers on neighboring firms. Similarly, the official opening in 1992 of a Mercedes-Benz AG facility in Rastatt was welcomed amidst great celebrations, and earned the participation of the then german Chancellor Helmut Kohl. Rastatt employment boomed not only in 1992, but also in 1997 and in 2004, the years chosen respectively for the start of large-scale production of the A and B-class Mercedes Benz series. It went less well in 2003 in Landshut and Wackersdorf, both home to large BMW factories: in that year, BMW employment dropped dramatically in response to the wave of strikes organized by IG Metall, the largest metalworkers union, dragging down total employment in both cities.

Despite the known local benefits, the presence of large players has also disadvantages, such as the induced higher volatility.[1] A recent strand of literature has revived the interest in the origins of volatility, by showing that the real impact of volatility shocks is large (Bloom (2009)). Starting with the seminal work by Gabaix (2011), *granularity-driven volatility*, or the volatility that arises due to lack of diversification of idiosyncratic shocks to large firms, has attracted considerable attention. We argue that it warrants more especially in light of the large number of studies documenting the rising role of large firms in the economy (De Loecker and Eeckhout (2017), Autor et al. (2017), Criscuolo et al. (2016)).

In this paper, we study the link between concentration and volatility by taking a spatial approach. There exists mostly narrative evidence to date supporting the existence of granularity-driven business cycles (Gabaix (2011)): the spatial variation exploited in this paper facilitates the development of an identification strategy aimed at filling this gap. The impact of granularity-driven shocks is moreover likely to be stronger at the local level due

[1] Another textbook disadvantage of a granular economy is the strengthened market power of the largest firms and higher inefficiency of the economy as a whole. The combination of granularity and oligopolistic competition has been for instance explored in Gaubert and Itskhoki (2018) and Grassi (2018).

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to the more likely failure of the law of large numbers.

The analysis presented in this paper is based on the real business cycle model in Carvalho and Grassi (2019) characterized by aggregate fluctuations that have a micro-origin. The closed-form expression for all the parameters governing the law of motion of aggregate employment makes their framework particularly amenable to empirical analysis. In order to take their model to the data, we require information at a business cycle frequency on the establishment size distribution. Proxies of concentration derived from a sample of firms - as typically available in most datasets - might be a poor approximation of the actual one: by the definition of fat-tailed distribution, an increasingly larger sample is needed to be able to observe the largest firms. Furthermore, the information contained in most firm-level datasets is at the yearly frequency, which is not enough a high frequency to conduct business cycle analysis. In this paper, we rely on the Administrative Wage and Labor Market Flow panel (AWFP) containing information on the size of each German establishment at the quarterly frequency since 1975. We focus on the period between 1990 and 2014 and on local labor markets located in former West Germany. Our baseline measure of local concentration corresponds to the fraction of local employment accounted by establishments situated above the 99^{th} percentile of the establishment size distribution in a given quarter.

In the first part of the empirical analysis, we provide evidence in favor of several empirical implications of the framework in Carvalho and Grassi (2019). First, we confirm that the higher is local concentration, the more persistent is local employment. Specifically, we find that a doubling in local concentration is associated with an increase in the autoregressive coefficient of local employment equal to its standard deviation. We moreover further confirm that the higher is establishment-level persistence, the more persistent is local employment. When economic activity in a given local labor market is concentrated enough, the economy becomes *granular*, meaning that the law of large numbers breaks down and a negative (positive) shock experienced by a disproportionately large firm does not get diversified away, thus causing local employment to drop or rise in tandem. Hence, local employment displays higher

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persistence in the presence of greater granularity, since it is more tied to shocks received by large firms, which are assumed to be persistent.

The second and main set of results pertains the relationship between local concentration and volatility. According to the just described mechanism, higher concentration increases the vulnerability of the economy to *granular* shocks, thus raising the conditional volatility of local employment. We construct an estimate of conditional volatility based on McConnell and Perez-Quiros (2000). According to our baseline specification, we find that 1% in local concentration is associated in a statistically significant way with an increase in the conditional volatility of local employment in the following period equal to $1/10^{th}$ of a percentage point, where moving from the 25^{th} to the 75^{th} percentile of the conditional volatility distribution entails an increase in conditional volatility equal to slightly less than one percentage point.

Can granularity give rise to business cycle fluctuations? To answer this question, we recast our results in the business cycle literature terminology. Specifically, we investigate whether concentration can predict the occurrence of local turning points. Our results suggest that higher local concentration is associated with a higher probability of a recession starting the following period. The correlation is not statistically significant for any other lag or lead of local concentration relative to the occurrence of local turning points. Furthermore, this result does not hold for the start of expansions. This result seems to suggest the rejection of the symmetry in Carvalho and Grassi (2019) on the equal likelihood of granularity to give rise to recessions and expansions alike. It also confirms the results found, for instance, in Baqaee and Farhi (2019) on the negative skewness induced by sectoral shocks in a non-linear business cycle model.

Next, we move to the calibration of the structural model. We calibrate a set of city-invariant parameters, and we derive the remaining ones by estimating the model-based law of motion of local employment separately for each city. The estimation requires the calibration of local productivity, the discretization of the establishment size distribution, and the construction of its (rescaled) second moment upon which conditional volatility depends.

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The city-specific parameters describe the cross-sectional productivity distribution: the support of the productivity distribution captured by the number of productivity improvements available in each city, and the probabilities of each individual establishment to grow, shrink or stay the same. Hence, they define two distinct sources of differences in aggregate productivity across cities. On the one hand, higher number of productivity improvements captures a static advantage: if the productivity distribution was uniform, a higher number of productivity improvements would be associated with higher aggregate productivity. On the other, a higher establishment growth probability captures a dynamic advantage: for a given number of productivity improvements, it implies that the fraction of establishments that will manage to climb the ladder of the productivity distribution up to its highest ranks is larger, so that aggregate productivity will also be higher.

The calibration of the structural model allows to quantify the contribution of granularity-driven fluctuations backed out from the model to local employment volatility. Granularity-driven volatility amounts to 50 basis points on average across local labor markets, while local employment volatility stands at 300 basis points on average. The correlation between the two measures across cities and years is 18%, with peaks of 30% in cities characterized by high levels of average concentration. Finally, our estimates suggest that the productivity premium of large cities is mostly shaped by a therein more right-shifted productivity distribution but also by a higher establishment growth probability. In particular, 1% increase in city size is associated with a 2 percentage points higher probability for an individual establishment to grow in productivity.

Literature review This paper touches primarily two strands of literature. The first is the one on the macroeconomic impact of granularity. Starting from the seminal work of Gabaix (2011), a number of studies have considered the impact of granularity with respect to several economic variables of interest: international trade (di Giovanni and Levchenko (2012), Gaubert and Itskhoki (2018)); competition (Gaubert and Itskhoki (2018) and Grassi

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(2018)); aggregate volatility (Carvalho and Gabaix (2013), Magerman et al. (2016), Carvalho and Grassi (2019)).

The analysis presented in this paper contributes to this literature by providing strong evidence supporting the view of granularity-driven business cycles. Secondly, we further unpack this result by testing the ability of granularity to give rise to recessions and expansions alike, and find strong evidence in favor of granularity-driven recessions only. This analysis underscores the need to further understand the role of large firms in starting - also by the effect of the network they operate in - a recession, but warns against claiming that a positive shock to a large firm can trigger an expansion.

The second strand of literature this paper is connected with is the one on the productivity premium of cities. Combes et al. (2012) and Gaubert (2018) focus on the agglomeration advantages for heterogeneous firms, while Behrens and Robert-Nicoud (2015) review the theoretical foundations of agglomeration economies in the presence of heterogeneous agents. Existing papers have so far tended to ignore the issue of differences in firm dynamics across cities, so that the higher aggregate productivity in large cities delivered by most of economic geography and urban economics models is often the result of exogenous differences in the cross-sectional productivity support together with endogenous selection/agglomeration mechanisms. By introducing idiosyncratic uncertainty, this is the first paper to disentangle the contribution of static, such as differences in the cross-sectional productivity support, vis-à-vis dynamic sources of the productivity premium in large cities, such as differences in the establishment growth probability. The analysis echoes the conclusions in De La Roca and Puga (2017) on workers learning in large cities and Duranton and Puga (2001) on firms learning in large cities.

Finally, while the notion of industry-level granularity has long been part of the debate on the destiny of cities and regions being tied to the one of industries in which they specializes, much less is known of the contribution of individual firms to the boom and bust cycles

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experienced by certain areas.[2] In this paper we take a first step towards providing an empirical answer to this question.

The paper proceeds as follows: Section 2 succinctly describes the theoretical framework on which the analysis is based; Section 3 provides the reduced-form evidence; Section 4 discusses narrative evidence; Section 5 presents the quantitative results; Section 6 concludes.

2 Conceptual Framework

In this section, we briefly sketch the setup in Carvalho and Grassi (2019) (henceforth CG 2019) and their main theoretical findings.[3] We assume that each local labor market or city is a rescaled version of their national economy.

The local state variable at time t in a representative local economy corresponds to the productivity distribution $\mu_t = (\mu_{1,t}, \mu_{2,t}, ..., \mu_{s,t}, ..., \mu_{S,t})'$, where $\mu_{s,t}$ denotes the number of firms at time t characterized by productivity φ^s. The productivity space is a S-tuple $\Phi = \{\varphi^1, ..., \varphi^S\}$, where $\varphi > 1$ so that $\varphi^1 < ... < \varphi^S$. Any given period, each of the N firms, with $N \in \mathbb{N}$, maximises profits by choosing labor input l given their idiosyncratic productivity, φ^s, and the local state variable, μ, according to:

$$\pi(\mu, \varphi^s) = \max_n \{\varphi^s l^\alpha - w(\mu)l\} \tag{1}$$

where $\alpha < 1$ captures the degree of decreasing returns to scale. Solving for the firm's maximization problem allows to derive labor demand $L_t^d = \left(\frac{\alpha}{w_t}\right)^{\frac{1}{1-\alpha}} A_t$, where local productivity is obtained by summing across firm productivities and it depends on the productivity

[2]Famous examples are the demise of the UK textile industry or the US car industry and the ensuing surge in unemployment and negative growth experienced in the North of England or the Midwest in the US. In a similar flavor to the one in this paper, Simon (1988) discusses the impact of industrial diversity on local labor market volatility, unemployment and wages.

[3]Since in the empirical analysis section we do not distinguish between the intensive (growth of continuing establishments) and extensive (entry/exit of establishments) margin of economic activity, we focus on the set of results in CG 2019 that are based on the absence of entry/exit.

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distribution through:

$$A_t = \sum_{s=1}^{S} (\varphi^s)^{\frac{1}{1-\alpha}} \mu_{t,s} \tag{2}$$

The model is closed by a ad hoc supply schedule $L_t^s = M w_t^\gamma$, with M being a scaling factor, such that the equilibrium wage and employment at time t are, respectively: $w_t = \left(\alpha^{\frac{1}{1-\alpha}} A_t\right)^{\frac{1-\alpha}{\gamma(1-\alpha)+1}} M^{\frac{\alpha-1}{\gamma(1-\alpha)+1}}$ and $L_t = \left(\alpha^{\frac{1}{1-\alpha}} A_t\right)^{\frac{\gamma(1-\alpha)}{\gamma(1-\alpha)+1}} M^{\frac{1}{\gamma(1-\alpha)+1}}$.

Switching to the dynamics of the model, each firm's productivity is assumed to follow a Markov chain with transition matrix P given by:

$$P = \begin{bmatrix} a+b & c & 0 & ... & ... & 0 & 0 \\ a & b & c & ... & ... & 0 & 0 \\ ... & ... & ... & ... & ... & ... & ... \\ 0 & 0 & ... & ... & a & b & c \\ 0 & 0 & ... & ... & 0 & a & b+c \end{bmatrix} \tag{3}$$

Hence, the probability of a firm's productivity to improve is c, to decline is a, to stay the same is $b = 1 - a - c$. Cordoba (2008) proves that the Markovian process described in eq.3 leads to a Pareto distribution, thus generalizing the continuous state-space result. For a given firm i characterized by productivity level $\varphi^{s_{i,t}}$, as $t \to \infty$ the probability of having productivity level φ^s is:

$$\lim_{t\to\infty} P(\varphi^{s_{i,t}} = \varphi^s) = K(\varphi^s)^{-\delta} \tag{4}$$

where K is a normalization constant and $\delta = \frac{log(a/c)}{log\varphi}$ is the tail index of the Pareto distribution to which the Markovian process described in eq.3 converges. As the probability of receiving a favorable shock c rises relative to the probability of receiving an unfavorable shock a the tail index declines and the firm size distribution becomes more fat-tailed.

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CG 2019 show that aggregate (local in our case) productivity follows the law of motion:

$$A_{t+1} = \rho A_t + O_t^A + \sigma_t \varepsilon_{t+1} \tag{5}$$

with:

$$\rho = a\varphi^{-\frac{1}{1-\alpha}} + b + c\varphi^{\frac{1}{1-\alpha}} \qquad \sigma_t^2 = \varrho D_t + O_t^\sigma \tag{6}$$

where $D_t = \sum_{s=1}^{S} \left((\varphi^s)^{\frac{1}{1-\alpha}} \right)^2 \mu_{s,t}$ is proportional to the second moment of the firm size distribution at time t. Hence, volatility of the local productivity shock $\tilde{\varepsilon}_{t+1} = \sigma_t \varepsilon_{t+1}$ is time-varying and proportional to the dispersion in the firm size distribution, D_t.[4]

Defining with $\widehat{X}_t$ the percentage deviation of variable X from its steady state, the law of motion for local employment is:

$$\widehat{L}_{t+1} = \rho \widehat{L}_t + \kappa \widehat{O}_t^A + \psi \frac{\sigma_t}{A} \varepsilon_{t+1} \tag{7}$$

where $\widehat{L}_t = \psi \widehat{A}_t$, with $\psi = 1 - \frac{1}{\gamma(1-\alpha)+1}$, $\kappa = \psi \frac{O^A}{A}$ and A equal to the steady state productivity level. Furthermore, ρ denotes the persistence of local employment.

Proposition 3, Carvalho and Grassi (2019). *If $\delta(1-\alpha) \geq 1$, then the persistence of local employment, ρ, satisfies the following properties:*

a. *Holding δ constant, local employment persistence is increasing in firm-level persistence b: $\frac{\partial \rho}{\partial b} \geq 0$,*

b. *Holding b constant, local employment persistence is decreasing in the tail index of the stationary productivity distribution: $\frac{\partial \rho}{\partial \delta} \leq 0$,*

c. *If the productivity distribution is Zipf, local productivity dynamics contain a unit root: if $\delta = 1/(1-\alpha)$, $\rho = 1$.*

[4] O_t^A and O_t^σ are two correction terms that vanish as the bounds of the productivity space increase, $E(\varepsilon_{t+1}) = 0$ and $Var(\varepsilon_{t+1}) = 1$. See CG 2019 (Online Appendix) for their definition.

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Proposition 3 (CG 2019) states that the dynamics of local employment in an economy characterized by a very skewed firm size distribution should feature a higher degree of persistence, holding firm-level persistence constant (b). Through the lenses of the theory, an increase in the degree of skewness holding firm-level persistence constant is achieved through an increase in the probability for an individual firm to grow matched by a tantamount decrease in the probability of shrinking. Additionally, it states that if firm-level persistence increases, higher persistence of local employment follows (a).[5]

Furthermore, CG 2019 demonstrate that the *conditional* (conditional on previous period employment) volatility of local employment is:

$$Var(\widehat{L}_{t+1}) = \psi \frac{\sigma_t^2}{A^2} = \psi \left(\varrho \frac{D}{A^2} \frac{D_t}{D} + \frac{O^\sigma}{A^2} \frac{O_t^\sigma}{O^\sigma} \right) \tag{8}$$

Proposition 4, Carvalho and Grassi (2019). *Then:*

a. *If* $1 < \delta(1-\alpha) < 2$ *, the unconditional expectation of the conditional variance of local employment satisfies:*

$$\mathbb{E}\left(\frac{\sigma_t^2}{A^2}\right) \sim_{N\to\infty} \frac{\varrho G}{N^{2\left(1-\frac{1}{\delta(1-\alpha)}\right)}}$$

where G *is a function of other parameters and independent of* N*,*

b. *The dynamics of conditional variance of local employment depend on the dispersion of firm size,* $\frac{\partial Var(\widehat{L}_{t+1})}{\partial D_t} > 0$*.*

Proposition 4 (CG 2019) states that the unconditional expectation of the conditional variance is an increasing function of the degree of skewness of the firm size distribution (a) and that the conditional variance is an increasing function of the degree of dispersion in the previous period (b).

Before moving to the empirical analysis, we briefly discuss two assumptions on which the interpretation of our reduced-form results hinge, namely the absence of movement of

[5] Carvalho and Grassi (2019) derived all their results in terms of aggregate output. Due to output isoelasticity in employment, their findings extend straightforwardly to aggregate employment.

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people and goods, both representing potentially important risk-sharing mechanisms across cities. Lack of short-run geographical mobility does not represent in our view a problematic assumption, since empirically it has been shown that mobility across local labor markets takes place primarily at low frequencies. The seminal work by Blanchard and Katz (1992) shows that the effect of a state-level employment shock on the employment rate disappears within seven years. Amior and Manning (2018) find even smaller responses of population to local labor demand shocks. The evidence on geographical mobility in response to local labor market shocks in the European Union is surveyed in Janiak and Wasmer (2008), where, applying the same methodology as in Blanchard and Katz (1992), it is shown that local labor market adjustments in the European Union tend to operate through changes in the labor market participation rate more than through geographical mobility. Further German-specific evidence supporting this assumption in provided in the Online Appendix.

On the contrary, we believe that the absence of trading relationships between firms in our model could pose potentially more serious problems to the interpretation of our results. However, we are forced to make this assumption due to lack of data on firm linkages. Large firms are more likely to engage in export activity (Melitz (2003)), so that we would expect that local employment is more exposed to the international cycle and hence more volatile in more granular cities. At the same time, though, firms integrated in global value chains are characterised by lower volatility (Kurz and Senses (2016)). This would seem to suggest that large firms pool and diversify different sources of risk (e.g., the internal risk associated with fluctuations in productivity, the risk associated with fluctuations in local wages, the risk associated with demand in the different markets where they operate), thereby reducing local employment volatility in more granular cities. Hence, the two just described mechanisms bias our estimates in opposite directions, but it is not possible with the data at our disposal to determine which of the two dominates.

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3 Empirical Evidence

The goal of the empirical section is first to test the following theoretical results in CG 2019:

1. higher persistence in establishment size is associated with higher persistence of local employment (Prediction 3a);

2. higher steady state local concentration is associated with higher persistence of local employment (Prediction 3b);

3. higher steady state local concentration is associated with higher unconditional expectation of the conditional volatility of local employment (Prediction 4a);

4. an increase (decrease) in local concentration leads an increase (decrease) in the conditional volatility of local employment (Prediction 4b).

After having analyzed the relationship between the moments of the local employment time series and the shape of the city-specific establishment size distribution, we establish a bridge between our results and the business cycle literature. Specifically, we investigate in the second part of the empirical analysis whether concentration can predict the occurrence of the local turning points marking the start of recessions or expansions.

3.1 Data

The analysis is based on the Administrative Wage and Labor Market Flow Panel (AWFP), a dataset on labor market flows and stocks for the universe of German establishments. The main data source of the AWFP is the Employment History (Beschäftigten-Historik, BeH) of the Institute for Employment Research (IAB). The BeH comprises employment information on all individuals which were employed subject to social security in Germany since 1975.[6] From the BeH, the AWFP aggregates the worker and job flow information to the establishment level. Before this aggregation, the data on individuals undergo several

[6] Since 1999 the BeH also comprises information on marginal part-time workers.

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validation procedures. The AWFP covers the time period 1975-2014 and it is available at a quarterly and an annual frequency (Stüber and Seth (2017)).

To ensure consistency over time, most variables in the AWFP are calculated on a "regular worker" basis. In the AWFP, a "regular worker" is defined as a person which is employed full-time and belongs to one of the following person groups: "employees subject to social security without special features", "seamen" or "maritime pilots". Therefore (marginal) part-time employees, employees in partial retirement, interns, etc., are not counted as regular workers.

For our analyses, we use the AWFP for the period from 1990q1 to 2014q4 at the quarterly frequency and restrict it to establishments from former West-Germany (excluding Berlin), to avoid a break in the series.[7] Further we restrict our sample to the universe of establishments with at least one regular worker and exclude establishments from two sectors of economic activity: Agriculture and Mining and the Public Sector (i.e., Public Administration and Health and Education). We retain exclusively establishments located in counties mapping into local labor markets of former West Germany.[8] This leaves us with a total of 72 metropolitan areas as shown in Fig.1 of the Online Appendix. Rural counties are thus excluded from the analysis.

3.2 Methodology

Measuring local concentration Since the focus is on large establishments, in the baseline analysis we measure concentration with the fraction of employment in metropolitan area m accounted by establishments situated above the local 99^{th} percentile of the establishment size distribution in metropolitan area m at time t. Existing literature has documented how establishment size is complementary with the size of the local labor market (Combes et al. (2012) and Gaubert (2018)). We document this empirical regularity also for German cities

[7]Data of establishments located on the territory of former East-Germany is included in the AWFP from 1993 onwards. With the inclusion of these establishments, we cannot distinguish between establishments located in former East-Berlin and West-Berlin anymore.

[8]The full list of metropolitan areas, or Functional Urban Areas in Eurostat terminology, for all European countries is available at http://ec.europa.eu/eurostat.

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in Table 1: a 1% increase in city size translates into a 3.5 percentage point increase in concentration as defined above. The magnitude of the coefficient increases when moving from the 90^{th} to the 99^{th} percentile.

In the baseline analysis, we seasonally adjust the local concentration time series in metropolitan area m using the procedure employed by Chodorow-Reich and Wieland (2020).[9] In the robustness section, we test the robustness of our results using directly the raw data. Based on the seasonally adjusted series, we find evidence of a downward trend in local concentration across all metropolitan areas in the sample: in Fig.2 in the Online Appendix we plot the median, the 10^{th} and 90^{th} percentile of the cross-sectional distribution of local concentration at any point in time during 1990q1-2014q4. This finding is in line with Moral-Benito and Queirós (2018) who also document that concentration has gone down among the population of Spanish firms. To account for the downward trend in local concentration, in the baseline analysis we linearly detrend the (log of the) seasonally adjusted local concentration time series separately for each metropolitan area m in the sample. We denote with $x_{m,t}$ seasonally adjusted and linearly detrended local concentration in metropolitan area m and time t and with $\overline{x}_m$ the constant term obtained from running a regression of (the log of) seasonally adjusted local concentration on an intercept and linear trend:

$$\text{s.a. concentration}_{m,t} = \overline{x}_m + \text{linear trend}_m + x_{m,t} \quad \forall m \tag{9}$$

In the robustness section, we test the robustness of our results to HP-filtering as an alternative detrending method.

Measuring local volatility Local labor market volatility is measured based on local employment. We apply the same data transformation to local employment as we did for local concentration, namely we seasonally adjust and linearly detrend (the log of) the seasonally adjusted local employment time series separately for each metropolitan area m in the sample

[9]The code has been kindly made available by the authors at: https://scholar.harvard.edu/chodorow-reich/data-programs.

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and denote it with $y_{m,t}$. This represents our baseline series for local employment. In the robustness section, we test the robustness of our results to alternative data transformations. Depending on the detrending method adopted (whether linear detrending or HP-filtering), detrended local employment may still feature a unit root. According to an augmented Dickey-Fuller test, the null hypothesis of a unit root cannot be rejected for the 98% of the local employment series when a linear detrending method is applied. The fraction of series for which it cannot be rejected drops to 41% when a HP-filtering method is applied. Hence, our baseline results - with the exception of those concerning the relationship between local concentration and local employment persistence - build on the assumption of the presence of a unit root in local employment and works with the first difference of seasonally adjusted and linearly detrended local employment, $\Delta y_{m,t}$.

Testing the predictions of Carvalho and Grassi (2019) Under an alternative transformation of the data such as HP-filtering, we can estimate local employment persistence as captured by the autoregressive parameter, ρ_m, obtained by fitting a AR(1) process on $y_{m,t}^{HP}$. Prediction 3a and 3b are tested by regressing $\widehat{\rho}_m$ on average local concentration $\overline{x}_m$ in eq.9 and an estimate of establishment-level persistence, $\widehat{b}_m$, obtained by fitting a AR(1) process for establishment size on the sample of establishments considered in each metropolitan area m individually considered.

In order to test Prediction 4a and 4b, we need to define a measure of local labor market time-varying volatility, or instantaneous volatility. We set instantaneous volatility in metropolitan area m and time t equal to $\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$ - a definition adopted also by McConnell and Perez-Quiros (2000), Carvalho and Gabaix (2013) - where $\widehat{\epsilon}_{m,t}$ is the innovation of the $I(1)$ process $y_{m,t} = y_{m,t-1} + \widehat{\epsilon}_{m,t}$.

First, we test Prediction 4a by regressing $\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$ on $\overline{x}_m$ in eq.9. Next, we test Prediction 4b by running:

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$$\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}| = \kappa_m + \kappa_t + \varphi x_{m,t-1} + \eta_{m,t} \tag{10}$$

The inclusion of year/quarter fixed effects in eq.10, κ_t, controls for changes in macroeconomic volatility, while city fixed effects, κ_m, allow for cross-city differences in average instantaneous volatility. A positively and statistically significantly estimated φ in eq.10 provides direct evidence that local concentration Granger-causes local employment volatility, thus confirming Prediction 4b.

Local business cycle analysis The second part of the empirical analysis looks at the concentration-volatility nexus from a business cycle perspective. For some academics and policy-makers in fact volatility is a variable of interest insofar as it is associated with recessions and recoveries. In what follows, we draw on the empirical business cycle literature to define the key variables of interest used in this second part of the empirical analysis.

The bulk of the literature on business cycle dating draws inspiration from the seminal work by Burns and Mitchell (1946). Their empirical definition of business cycle goes as follows: *"business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle."*

Hence, there are two peculiar features of business cycles: 1) the comovement of many individual economic series, and 2) the different behavior of the economy during expansions and contractions (Diebold and Rudebusch (1996)). In this paper, we focus on the second feature of business cycle fluctuations. We identify local and aggregate business cycles by means of the widely exploited Harding and Pagan (2002) business cycle dating algorithm. A business cycle is defined as the period ranging from peak to next peak: within a business cycle we distinguish two phases, a recession (lasting from peak to next trough) and a recovery (lasting from trough to next peak). We apply the same censoring rules as in the original

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paper by Harding and Pagan (2002): we impose that a business cycle lasts at least 5 quarters, and that a phase (either recession or recovery) lasts at least 2 quarters.

We assess the goodness of the business cycle dating algorithm applied to aggregate employment against the turning points identified by the OECD.[10] Aggregate employment is plotted in Fig.3 in the Online Appendix together with the start and end of recession dates identified according to the two procedures (OECD - left, Harding and Pagan (2002) - right). The downward trend observed at the national level is explained by the contemporary increase of part-time and marginal employment.[11]

The dating procedure identifies 413 local business cycles. The modal city has experienced during 1990-2014 six local business cycles. The number of business cycles at the local level ranges from three (7% of the sample of cities) to eight (14% of the sample) with an outlier city having experienced ten business cycles over the period considered. Table 1 in the Online Appendix provides summary statistics on local business cycle properties.

We test whether higher concentration is empirically associated with a higher probability of a local recession/recovery starting the following period, in 2 periods, etc., or having started the period before, 2 periods before, etc. We use a linear probability model to answer this question and regress therefore the probability of a peak (or a trough) taking place at time t in metropolitan area m on local concentration at time $t+k$ with $k \in (-4, +4)$:

$$
\begin{aligned}
P(t = \text{peak}_m) &= \alpha + \beta x_{m,t+k} + \gamma_m + \delta_t + \varepsilon_{m,t} \\
P(t = \text{trough}_m) &= \alpha + \beta x_{m,t+k} + \gamma_m + \delta_t + \varepsilon_{m,t} \qquad (11)
\end{aligned}
$$

where the presence of time fixed effects controls for aggregate shocks.

[10]Data on OECD-based turning points can be found at https://fred.stlouisfed.org/series/DEURECM.

[11]There are different potential explanations behind the discrepancy between the two sets of turning points. A first possible reason could be that the analysis in this paper is based on former West Germany only, while the OECD considers Germany as a whole. A second candidate explanation has to do with the economic indicator used for business cycle dating: the OECD relies on industrial production, which provides timely information on economic activity at the monthly frequency and for a large set of countries. while this analysis in this paper is based on aggregate employment only.

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3.3 Findings

Local concentration, local employment volatility and persistence Table 2 reports the coefficients of a linear regression of persistence of local employment, $\widehat{\rho}_m$, on establishment-level persistence (Prediction 3a) and average local concentration (Prediction 3b). As already mentioned, this is the only set of results for which we are forced to deviate from our baseline data transformation of seasonal adjustment and linear detrending and estimate $\widehat{\rho}_m$ based instead on seasonally adjusted and HP-filtered local employment. As we show below, none of our results hinges on the linear detrending vs. HP-filtering choice, and we retain the former as preferred transformation of the data because more transparent and also due to potential issues associated with HP-filtering the data (Hamilton (2018)). The estimates reported in Table 2 show that persistence of local employment depends positively and in a statistically significant way on both establishment-level persistence and average local concentration.

Table 3 reports the coefficients of a linear regression of average conditional volatility of local employment, $\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$, on average local concentration (Prediction 4a). The coefficient on average local concentration is positive and statistically significant only after the inclusion of city size as a control. When we control for (the log of) city size we find that a 1% increase in the fraction of local employment accounted by establishments situated above the 99^{th} percentile of local establishment size distribution is associated with an increase in average conditional volatility of .15 percentage points, where average conditional volatility in the sample is about .9 percentage points. While the inclusion of city size as a control is atheoretical in this context so that the result presented in Table 3 should not be seen strictly speaking as supportive of the theory tested in this paper, we point out that nevertheless a negative relationship between local volatility and city size arises in other models, e.g., those connected with risk-sharing (Duranton and Puga (2003)).

Next, we consider the dynamic relationship between conditional volatility and local concentration. In Table 4 we report the coefficients from estimation of eq.10. Regression results highlight a consistently positive and statistically significant association between lagged local

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concentration and instantaneous volatility, thus validating Prediction 4b. Specifically, we find that when a 1% increase in local concentration is associated with a .9 percentage points increase in instantaneous volatility the period after. Due to the possibility of contemporaneous correlation between $\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$ and $x_{m,t}$ that in the case of autocorrelation of $x_{m,t}$ would risk biasing the coefficient of interest, we add as a control $\Delta x_{m,t}$ in order to avoid including in the same regression two variables, $x_{m,t-1}$ and $x_{m,t}$, potentially highly correlated. The coefficient of interest, $\widehat{\varphi}$, remains positive and statistically significant also when adding $\Delta x_{m,t}$ as a control in eq.10.

Granularity-driven recessions only Finally, we provide a more accurate test on the Granger-causality linking concentration of economic activity to local business cycles. The estimated coefficients of eq.11 and corresponding 90% confidence intervals are reported in Fig.1. Quite strikingly, local concentration has a statistically significant and positive association exclusively with the probability of the economy entering a recession in the following period (left panel of Fig.1). The same does not hold true for the probability of entering an expansion in the following period (right panel of the same figure).

This evidence lends support to the view that the effects of granularity on aggregate volatility might be non-linear, confirming the existence of granularity-driven recessions *only*. There exist potentially many candidate explanations behind this asymmetry. For instance, it can be that while large negative fluctuations in a firm's workforce can be caused by exogenous idiosyncratic shocks, large positive fluctuations are more likely to be the result of purposeful decision-making at the firm level. In particular, when a firm expands, it expands, for instance, because it has developed a significantly better technology. Hence, it expands at the expenses of its competitors, some of which are located in the same local labor market, and whose market share and therefore labor demand drops. While it is outside the purpose of this paper to provide a rigorous explanation for the just found asymmetry, we believe the answer can be found by combining random growth theory for what concerns large downsizes

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in a firm's production with the insights from endogenous growth as in Aghion and Howitt (1992) for what concerns large positive improvements in a firm's production. Alternatively, a recent contribution by Baqaee and Farhi (2019) shows that in a business-cycle calibration with sectoral shocks, nonlinearities (e.g., network linkages and heterogeneity in elasticities of substitutions or returns to scale) magnify negative shocks and attenuate positive shocks, resulting in an aggregate output distribution that has negative skewness.

3.4 Robustness

In this section, we investigate the robustness to: 1) alternative data transformations, 2) sample selections, 3) alternative measures of concentration. We start by replicating the analysis summarized in Table 4 using just linearly detrended local concentration and employment, thus skipping the seasonal adjustment step. It could be argued that there are no strong arguments in favor of a seasonal pattern in the local concentration series unless firms tend to hire/fire workers only in given times of the year, which is likely to be the case but only for certain industries/size classes. The second bar in Fig.2 features the estimated coefficient on $x_{m,t-1}$ in eq.10, $\widehat{\varphi}$, under this alternative transformation of the data. Next, we consider HP-filtering as an alternative detrending method for both local concentration and employment after having seasonally adjusted both series. HP-filtering the local employment series eliminates a large fraction of unit roots in the data according to an augmented Dickey-Fueller test as discussed in the previous section. For this reason, under this alternative transformation of the data we estimate instantaneous volatility by fitting a AR(1) process on $y^{HP}_{m,t}$ and set instantaneous volatility, $\widehat{\epsilon}_{m,t}$, equal to the residual. Similarly, we replace in eq.10 $x_{m,t}$ - obtained from linearly detrending the log of seasonally adjusted local concentration as in eq.9 - with $x^{HP}_{m,t}$ obtained from HP-filtering the log of seasonally adjusted local concentration. The estimated coefficient of interest on $x_{m,t-1}$ in eq.10, $\widehat{\varphi}$, is the third bar in Fig.2, marginally higher than in the baseline.

Given an important sequence of labor market reforms introduced in Germany during

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2004-2005, also known as Hartz reforms, we consider splitting the sample in before and after 2005 to test heterogeneous effects in the coefficient of interest. The magnitude of the corresponding coefficients is captured by the height of, respectively, the fourth and fifth bar in Fig.2. The coefficient of interest is statistically significant only prior to 2005. There are at least two candidate explanations for such heterogeneity. The first one has to do with the fact that the Hartz reforms liberalized the labor market, making it easier for firms to enter more flexible contractual arrangements with their workers that are not captured in our full-time regular workers sample. The second candidate explanation has to do with the declining trend in local concentration shown in Fig.2 in the Online Appendix, which is such that average concentration in the post-Hartz reforms period is lower than in the period before. While we work with local concentration in deviation from the time trend, according to the theory outlined in Gabaix (2011) granular fluctuations emerge only for values of the firm size distribution tail close to one. It is therefore possible to be in a situation where the trend interacts with the cycle, so that lower absolute (not in deviation from the trend) average concentration in the post-Hartz reform period reduced the chances of idiosyncratic shocks to large firms to play out at the aggregate level.

Next, we consider an alternative measure of local concentration, given by the Herfindahl index $H_{m,t} = \sqrt{\sum_i s_{i,m,t}^2}$, where $s_{i,m,t}$ is firm i share of employment in metropolitan area m and time t. A higher Herfindahl index captures a less diversified local economy, therefore susceptible to higher volatility. We estimate the coefficient of interest, $\widehat{\varphi}$, after having replaced $x_{m,t-1}$ with $H_{m,t-1}$. The estimated coefficient is statistically significant and positive and it should be interpreted as the increase in volatility measured in basis points observed in the period after a unitary increase in the Herfindahl index, where a unitary increase corresponds to the range of this variable. The link between the Herfindahl index and volatility is also statistically significant when comparing average conditional volatility with the average Herfindahl index (third column of Table 5). Conversely, as already shown for the baseline evidence, average conditional volatility estimated via applying a HP-filter to local employ-

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ment does not depend in a statistically significant way on average local concentration proxied by the share of employment in top-99th percentile establishments (unless log of city size is controlled for) (second column of Table 5).

Further robustness checks, such as replicating the main result from the business cycle analysis under alternative data transformations or controlling for industry-level granularity, are also included in the Online Appendix.

4 Narrative Evidence

In the same spirit of Gabaix (2011), we provide in this section narrative evidence of the existence of granular business cycle at the local level. The characteristics of the German economy make it particularly well-suited to investigate the micro-origins of local business cycles, since it features a high number of large corporations active in the industrial goods/chemicals sector and with a dense network of establishments operating in Germany.[12]

We conduct a manual search of all German sites where the 15 companies belonging to either the chemicals or industrials goods sector are located. For each company we compile a list of counties where all German plants listed in the *careers* section of the company website are located. Where needed we supplement the search with information coming from Indeed.de, the popular vacancy advertising website, that allows to search for all vacancies posted by a specific company, grouping search results according to the location of advertised vacancies. The average number of German sites per company is 8, with substantial variation: while Bayer and BMW have 13 production facilities in Germany, Merck has only one, since most of the company's production takes place in the United States.

Next, we download for each company historical stock closing price data for regular shares

[12] Of the 30 companies that are included in the DAX index: 6 are active in the chemicals sector (BASF, Bayer, Beiersdorf, Henkel, Linde and Merck); 9 are active in the industrial goods sector (Adidas, BMW, Continental, Daimler, HeidelbergCement, Infineon Technologies, Siemens, ThyssenKrupp, Volkswagen Group); 2 in the energy sector (E.ON and RWE); 3 are government-owned companies (Deutsche Lufthansa, Deutsche Post, Deutsche Telekom); 2 in the medical sector (Fresenius and Fresenius Medical Care); 6 in the finance-insurance-real estate, or FIRE, sector (Allianz, Commerzbank, Deutsche Bank, Deutsche Börse, Munich Re, Vonovia); 1 in the media sector (ProSiebenSat.1 Media); 1 in the software industry (SAP).

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from Yahoo Finance at the weekly frequency. We seasonally adjust the series and calculate quarterly stock price growth rates.[13] Stock price data for a given company are matched to employment data for each county where the company has a production site. Finally, we calculate the correlation for each of the 113 company/county matched pairs. The median correlation is positive and in several instances statistically significant. Fig.3 reports both the company stock price growth rate and the local employment growth rate for 4 company/location pairs featuring the highest and statistically significant correlation between the two series.

BMW, *Landshut* and *Wackersdorf* factories The first and second plot of Fig.3 show BMW stock price evolution together with employment in Landshut (Bayer) and Wackersdorf (Bayer). Nowadays, Landshut factory has 4100 employees, while the Wackersdorf facility employs 3000 people.[14] Landshut population stands at around 70000 inhabitants, while average private sector full-time employment in AWFP data is 18000. Wackersdorf is part of *Schwandorf* county, which has population of 140000 and average employment in AWFP data of 30000.

In the first quarter of 2003 Landshut employment drops by 5%: this is the largest drop registered in Landshut over the entire sample. Schwandorf employment experiences a comparable drop in aggregate employment ($\approx 3\%$) anticipated by one year, hence during the first quarter of 2002. The period between the first quarter of 2002 until the second quarter of 2003 represents an unlucky spell for BMW stock as well: the closing price drops from 40.2 in 2002Q2 to 28.3 in 2003Q1.

What happened in 2002 that potentially drove down both BMW stock price and Landshut and Schwandorf employment? The first quarter of 2002 marks the start of a wave of strikes in Germany organized by IG Metall: the largest metalworkers union in Germany at that time demanded a shorter working week for factories located in the East, corresponding to

[13] The price is set in a given quarter equal to the price during its first week.
[14] See https://www.bmwgroup-werke.com/.

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a reduction from 38 to 35 weekly working hours, the latter being the number of working hours in place in West Germany factories. Disruptions in production were passed on to firms located further on along the supply chain, BMW being one of those. Newspapers articles report that several BMW production facilities in the first quarter of 2003 had to let go several thousands of workers for an unpredictable period of time.[15] In mid-2003 the strikes ceased, and both employment in Landshut and Schwandorf and BMW stock price rose again.

Beiersdorf, *Hamburg* site Beiersdorf AG is a German company active in the chemicals sector. It was founded in 1882 and it is headquartered in Hamburg, where it employed 3100 workers in 2003.

"In 2003, a 2-year bidding war ended. Procter & Gamble, an American competitor, had sought to purchase Beiersdorf and proposed a take-over deal to Allianz insurance, which then held 19.6% of Beiersdorf's stock. Fearing that Procter & Gamble was interested only in Beiersdorf's brands and not in the company as a whole, many in Hamburg preferred to retain local ownership. The city of Hamburg and its state-owned holding company HGV created such a solution. The Herz family, owner of the German company Tchibo, who already had a stake in Beiersdorf, increased their holdings to 49.9%. Allianz still held 3.6%; Beiersdorf AG bought up 7.4% of its shares, of which 3% were given to the Beiersdorf pension fund. Another share holder, a private family, retained their share. This public-private alliance ensured that Beiersdorf's headquarters would remain in Hamburg and continue to provide hundreds of jobs, while paying taxes of approximately €200 million annually."[16]

The fear of investors during this time of uncertainty is fully captured by the evolution of the stock price: Beiersdorf stock lost more than 25% of its value during 2002, dropping from 44 in 2002Q1 to 33 in 2002Q3. At the same time, one can see from the third plot in Fig.3 that in 2003Q4 a spell of negative employment growth that started in 2001Q3 finally

[15]See https://www.theguardian.com/world/2003/jun/21/germany.jeevanvasagar.
[16]See https://www.abendblatt.de/wirtschaft/article106724487/Sieg-fuer-Hamburg-Tchibo-und-Stadt-kaufen-Beiersdorf.html.

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came to an end: this period of time coincides with the one over which the take-over battle by Procter & Gamble took place.

One can imagine that during this time of heightened uncertainty and decline in global sales the company paused the hiring process and sought a contraction in its labor costs. The timing of events and the importance of Beiersdorf for the local economic environment provide good proof of the causal link between the difficulties experienced by Beiersdorf in 2002/2003 and the long spell of subdued employment growth the city of Hamburg went through during the same period.

Daimler, *Rastatt* factory The Daimler AG plant in Rastatt nowadays employs 6500 employees and it is the lead plant in compact car production. Rastatt is a county located in Baden-Württemberg. It has a population of 227000 inhabitants, and average private sector full-time employment of 56000 in AWFP data. The history of this production plant can be taken as an example of positive idiosyncratic shocks having positive repercussions on local employment. In 1997, for example, employment in Rastatt grows by 3.5% over just two quarters. At the same time Daimler AG stock price rises by 42%, from 59 in 1997Q1 to 84 in 1997Q3. What happened during these two miraculous quarters? Large-scale production of the Mercedes-Benz A-Class kicked-off in June 1997: by the time production started, the Rastatt plant was employing just under 4000 people, almost twice as many as it had in October 1996. Similarly, in 2004 Mercedes-Benz announced the start of B-Class production in the Rastatt plant: in 2004Q3 Rastatt aggregate employment grows by 1.4%, against an average growth rate of nearly zero over the 25 years considered.

The narrative just presented shows that it is possible to identify episodes of large stock market volatility for specific German companies that turned out to be accompanied by high local employment volatility in cities where these companies had their plants. A manual research on the sources of such heightened stock market volatility confirms that on such occasions companies were going through moments of turmoil that reflected in their hiring/firing

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and therefore overall employment levels. The phases of restructuring/expansion that these companies went through had significant consequences for the overall employment level in the local labor market where they had their production plants.

5 Quantitative Results

In Section 3, we showed how local concentration of economic activity, which was treated as a given, is on average higher in larger local labor markets. In this section we disentangle the sources behind the more fat-tailed size distribution in bigger cities by calibrating the parameters governing firm dynamics in each city.

5.1 Calibration

The calibration of the structural parameters is conducted separately for each metropolitan area and it is based on the model sketched in Section 2. Each city is characterized by a set of structural parameters, some of which are assumed to be common across cities. Specifically, the city-specific parameters are $\Theta_m = \{a_m, b_m, c_m, S_m\}$, hence, respectively, the probability of shrinking/staying the same/growing, and the number of steps in the productivity distribution. The shape parameter of the productivity distribution, $\delta_m = \frac{log(a_m/c_m)}{log(\varphi)}$, is therefore also city-specific. The set of remaining parameters are assumed to be city-invariant, $\Xi = \{\alpha, \gamma, \varphi\}$, hence, respectively, the parameter governing the returns to scale, the labor supply elasticity and the log step in the productivity distribution.

We restrict our focus to 60 quarters, i.e., those spanning the period between 1990 and 2004, during which the impact of granularity on aggregate volatility is most significant (Fig.2). The calibration procedure is as follows. First, we construct a sparse grid for the three city-invariant parameters.[17] For each combination on this grid: 1) we calibrate the

[17] We specify the following grid for the three city-invariant parameters. We set $\gamma = \{.5, 1, 2\}$. The interpretation of this parameter is different from the one in a model with hours worked. In this model, $1 + \gamma$ is the elasticity of indirect utility to the local wage, i.e., the supply elasticity to wages in a spatial equilibrium setup. Estimates of this elasticity oscillate around 3 for the U.S. (Diamond (2016)). Given that mobility in

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city-specific number of steps, S_m; 2) we derive aggregate productivity, A_{mt}, and use it to get the sequence of employment steps, $l_{mt} = [l_{1,mt}, l_{2,mt}, ..., l_{S,mt}]$, for each city m and time t; 3) we count the number of establishments located in each employment bin and use it to construct a series for D_{mt}, which is proportional to the second moment of the establishment size distribution in city m and time t; 4) given the law of motion for aggregate employment in city m we estimate ρ_m and ϱ_m in each city and use them to calculate a_m, b_m, c_m and the implied δ_m. Finally, we select the combination of city-invariant parameters, Ξ, that minimizes the mean squared error between reduced form estimates of δ_m and the model counterparts.

Calibrating the city-specific number of steps S_m We start by calculating the employment share of the largest establishment in each city and quarter and take the average over the period considered, $share_{S,m}$. We then look for the integer value S_m that minimizes $\left(share_{S,m} - \frac{\varphi^{S_m/(1-\alpha)}}{A_m}\right)^2$ for each city m, where A_m corresponds to steady state aggregate productivity in city m, whose closed-form expression is:[18]

$$A_m = N_m \varphi^{1/(1-\alpha)} \frac{1-\varphi^{-\delta_m}}{1-\varphi^{-\delta_m S_m}} \frac{1-\varphi^{(1/(1-\alpha)-\delta_m)S_m}}{1-\varphi^{1/(1-\alpha)-\delta_m}} \tag{12}$$

During this stage of the calibration process we set δ_m equal to its reduced form estimate, corresponding to the coefficient estimated by running a log rank-log size regression on the truncated sample corresponding to the upper 10^{th} percentile of the city-specific establishment size distribution for an intermediate sample year ($t = 2000$), an approach known to the related literature (Agustí and Teruel (2012)).

the U.S. tends to be higher than in European countries, we consider also lower values for this parameter. For the remaining two city-invariant parameters, α and φ, we consider a denser grid centred around the values used in the calibration exercise by CG 2019, $\alpha = .8$ and $\varphi = 1.0874$.

[18] We set the number of establishments equal to the average establishment count in each city.

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Calibrating the employment steps in each city and quarter The s^{th}-step establishment employment in city m and time t is::

$$l_{s,mt} = \frac{\varphi^{s/(1-\alpha)}}{A_{mt}} L_{mt}^{data} \tag{13}$$

where aggregate productivity in city m and time t is backed out from the data and set equal to:

$$A_{mt}^{data} = \left(\frac{(L_{mt}^{data})^{(\gamma(1-\alpha)+1)/\gamma}}{\alpha N_m^{1/\gamma}} \right)^{1/(1-\alpha)} \tag{14}$$

Calibrating the dispersion in establishment employment shares An establishment i in city m and time t is assumed to be in bin s if $l_{i,mt} \leq l_{s,mt}$ and $l_{i,mt} > l_{s-1,mt}$. We adopt an approximation and include in the last bin, S_m, all establishments such that $l_{i,mt} > l_{s-1,mt}$.[19] Using the thus obtained series of establishment counts for each productivity step, $\mu_{s,mt}$, we calculate D_{mt}, which is proportional to the second moment of the establishment size distribution:

$$D_{mt} = \sum_{s=1}^{S_m} \mu_{s,mt} \varphi^{\frac{2s}{1-\alpha}} \tag{15}$$

Estimation of ρ_m and ϱ_m Ignoring the correction terms, the law of motion for the log deviation from steady state of aggregate employment in city m is:

$$\widehat{L}_{m,t+1} = \rho_m \widehat{L}_{m,t} + \psi \frac{\sqrt{\varrho_m D_{mt}}}{A_m} \varepsilon_{m,t+1} \tag{16}$$

where the distribution of $\varepsilon_{m,t+1}$ can be approximated by a standard normal distribution. Then, redefining $\widehat{L^*}_{m,t+1} = \widehat{L}_{m,t+1} \times \frac{A_m}{\psi\sqrt{D_{mt}}}$ and $\widehat{L^*}_{m,t} = \widehat{L}_{m,t} \times \frac{A_m}{\psi\sqrt{D_{mt}}}$, the values of ρ_m and

[19] An alternative would have been to apply the same approximation to the first bin, instead of the last one. The outcome of the calibration is not sensitive to this choice.

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ϱ_m are easily estimated via OLS:

$$\widehat{\rho}_m = \frac{\sum_t \widehat{L^*}_{m,t+1}\widehat{L^*}_{m,t}}{\sum_t \left(\widehat{L^*}_{m,t}\right)^2} \qquad \widehat{\varrho}_m = \frac{1}{T}\sum_t \left(\widehat{L^*}_{m,t+1} - \widehat{\rho}_m \widehat{L^*}_{m,t}\right) \tag{17}$$

The probabilities of shrinking and growing in each city, a_m and c_m respectively, can be backed out given $\widehat{\rho}_m$ and $\widehat{\varrho}_m$:

$$\widehat{a}_m = \frac{-\widehat{\varrho}_m + (\widehat{\rho}_m - 1)(\chi + 1) + (1 - \widehat{\rho}_m^2)}{(\omega - 1)(\chi - \omega)} \qquad \widehat{c}_m = \frac{\widehat{\varrho}_m - (\widehat{\rho}_m - 1)(\omega + 1) - (1 - \widehat{\rho}_m^2)}{(\chi - 1)(\chi - \omega)} \tag{18}$$

with $\chi = \varphi^{1/(1-\alpha)}$ and $\omega = \varphi^{-1/(1-\alpha)}$.[20]

5.2 Results

We start by commenting the calibrated city-invariant moments. Our results are substantially aligned with CG 2019 concerning the calibration of the returns to scale, $\alpha = .825$. Next, we calibrate $\gamma = 1$, therefore lower than CG 2019, where it was set equal to 2. Since our estimation is based on per capita employment rather than hours worked, we argue that the correct range of estimates against which this value should be assessed is not the one for the Frisch elasticity, but rather existing estimates of the labor supply elasticity to wages in spatial equilibrium models (e.g., Diamond (2016)). These estimates tend to be centred around the value of 3, hence, above our calibrated value of $1 + \gamma = 2$. This difference can be rationalized in terms of much weaker internal mobility in Germany (and other European countries) relative to the U.S. Finally, we set the log step of the productivity distribution, φ, equal to 1.15, higher therefore than 1.0874 as CG 2019.

The fit of the model is assessed with respect to the targeted moment of the distribution of shape parameters across cities. The distribution in the data and in the model are plotted

[20] The probabilities might not all be bounded between 0 and 1. For this reason, we impose a constraint on the minimization problem, and look for an optimum such that the probabilities are positive and bounded between 0 and 1 for at least $N \geq 50$ cities.

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in the left panel of Fig.4, and the Pearson correlation coefficient is 27%. The model overestimates by a factor of three the dispersion of city-specific shape parameters and it delivers an average shape parameter of 1.4 against 1.17 in the data. This underestimation of the degree of concentration of economic activity in cities is understandable as not all local volatility is due to granularity: the model is therefore unable to match punctually the magnitude of the average shape parameter in the data since this would deliver counterfactually too high granularity-driven local volatility.

Given the set of calibrated parameters for each city in the sample, we calculate the explanatory power of model-implied local volatility with respect to volatility as measured in the data according to $\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$, with $\widehat{\epsilon}_{m,t} = \Delta y_{mt}$. Model-implied local volatility is $\widehat{\sigma}_{L,m,t} = \left(1 - \frac{1}{\gamma(1-\alpha)+1)}\right) \frac{\widehat{\sigma}_{A,m,t}}{\widehat{A}_m}$ with $\widehat{A}_m = A_m(\widehat{S}_m, \widehat{\delta}_m)$ as in eq.12 and $\widehat{\sigma}_{A,m,t} = \widehat{\varrho}_m D_{mt}$, where D_{mt} is backed from the data given the calibrated city-invariant parameters $\{\alpha, \varphi\}$ according to eq.15. The Pearson correlation coefficient between time-varying volatility in the data and in the model is 18%. Moreover, the correlation is as high as 30% in cities with estimated lower shape parameter (Fig.5), thus underscoring the superior capability of the model at replicating business cycle fluctuations in cities characterized by greater granularity.

The cross-sectional productivity distribution can result into firms being on average more productive in a city compared to another one not only because firms are therein born on average more productive, but also because they enjoy a greater chance of scaling-up. Fig. 6 shows how different city-specific parameters vary with city size: the only parameters that vary in a statistically significant way with city size are the number of productivity steps, S_m, and the probability of growing, c_m. Specifically, a 1% increase in city size translates into a 2 percentage points higher probability of growing. This gradient in city size is substantial given that the median probability of growing is 13% (Table 3 of the Online Appendix). On the other hand, an establishment located in a small city does not face necessarily higher odds of shrinking relative to an establishment located in a large city.[21]

[21] One alternative explanation for the correlation between probability of scaling-up and city size is sectoral composition. Large cities tend to be specialized in ICT industries that are characterized by a higher incidence

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To find out the relative importance of different components in shaping the productivity premium of large cities, we calculate average productivity (thus rescaling model-implied aggregate productivity as of eq.12 by the number of firms active in each city) letting either only S_m or only c_m vary, while holding therefore, respectively, c_m/a_m and S_m/a_m fixed. In the first case, we find that doubling city size translates into an increase in average productivity of 2%, below the range of estimates of 4%-8% found in Rosenthal and Strange (2004). When we let only the probability of establishment growth vary across cities, the estimated premium is 30%, thus substantially higher than the upper bound of existing estimates. The latter estimate is in any case several orders of magnitude higher than the premium obtained by letting only the productivity distribution support vary, thus demonstrating how differences in the likelihood of firms' scaling-up across cities are a primary driver of the productivity premium in large cities. Concerning the overestimation, we argue that one candidate explanation has to do with the role of sorting of fast-growing firms into large cities, which is potentially biasing the results upwards. Disentangling the contribution of this type of sorting to the just documented source of productivity premium in large cities is a task that we leave for future research.

6 Conclusion

The presence of large firms generates local productivity gains but it also raises the local volatility. In this paper, we provided strong evidence in favor of granularity-driven business cycles. Next, we disentangled the sources behind the more fat-tailed size distribution in bigger cities.

With the support of quarterly data on the evolution of the concentration of economic activity across 72 metropolitan areas located in former West Germany over the past 25

of high-growth firms. At the same time, large cities tend to feature as well a larger share of young firms, which are known to grow on average more than old firms conditional on survival. We test both hypothesis. We calculate the average employment share into the ICT sector and the age of the average establishment for each city: we find that controlling for either variable does not change the conclusion of a higher probability of growing in large cities.

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years, we provided evidence supporting the main empirical implications of the theoretical framework developed in Carvalho and Grassi (2019) where business cycles arise due to idiosyncratic shocks to large firms that failed to get diversified away. When we unpacked this result by testing the ability of granularity to give rise to recessions and expansions alike, we found strong evidence in favor of granularity-driven recessions only.

Next, we calibrated the structural model in Carvalho and Grassi (2019) applied to each of the 72 metropolitan areas in the sample. Based on the calibrated parameters, we showed that the more fat-tailed productivity distribution observed in large cities is due to both a static productivity premium, i.e., the availability of a larger number of productivity improvements, and a dynamic productivity premium, i.e., the higher probability for an individual establishment located in large cities to climb up the productivity ladder.

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Appendices

A Tables

Table 1: City size and concentration.

	E-prop. above 99th pct.	E-prop. above 95th pct.	E-prop. above 90th pct.
Log size	0.034***	0.028***	0.021***
	(3.94)	(4.59)	(4.48)
Observations	72	72	72

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Complementarity between large establishments and large cities: E-prop. above x^{th}percentile$_m$ $= \alpha + \beta \ln \text{Size}_m + e_m$, where m indexes cities. Source: AWFP.

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Table 2: Determinants of local employment persistence.

	Dep.var.: $\widehat{\rho}_m$	
$\overline{x}_m$	0.029	0.033*
	(1.59)	(1.82)
$\widehat{b}_m$		1.114**
		(2.22)
Observations	72	72

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Local employment persistence in city m on establishment-level persistence (Proposition 3a); on average concentration (Proposition 3b). Aggregate employment persistence $\widehat{\rho}_m$ corresponds to $\ln(\text{employment})_{m,t}^{HP} = \text{constant}_m + \rho_m \ln(\text{employment})_{m,t-1}^{HP} + \varepsilon_{m,t}$ (estimated city-by-city) where $\ln(\text{employment})_{m,t}^{HP}$ is seasonally adjusted and HP-filtered local employment. $\overline{x}_m$ in eq.9. Finally, $\widehat{b}_m$ is establishment-level persistence in employment and it is obtained by fitting on the sample of establishments considered a AR(1) process on establishment size for each metropolitan area m individually considered. Source: AWFP.

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Table 3: Determinants of local employment average conditional volatility.

	Dep.var.:	$\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}\vert\widehat{\epsilon}_{m,t}\vert$
$\overline{x}_m$	-0.001	0.002**
	(-1.36)	(2.06)
$\ln(size)_m$		-0.001***
		(-7.11)
Observations	72	72

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Local employment average conditional volatility in city m on average concentration (Proposition 4a). Local employment average conditional volatility corresponds to average instantaneous volatility $\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{m,t}|$, where $\widehat{\epsilon}_{m,t} = \Delta y_{m,t}$. $\overline{x}_m$ in eq.9. Source: AWFP.

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Table 4: Instantaneous volatility and concentration of economic activity.

	Dep.var.: $\sqrt{\frac{\pi}{2}}\lvert\hat{\epsilon}_{m,t}\rvert$	
$x_{m,t-1}$	0.009***	0.008**
	(2.67)	(2.02)
$\Delta x_{m,t}$		-0.027*
		(-1.90)
Observations	7128	7128
R^2	0.302	0.304

t statistics in parentheses (robust), * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Estimation results of eq.10. $\sqrt{\frac{\pi}{2}}\lvert\hat{\epsilon}_{m,t}\rvert$ corresponds to instantaneous volatility, where $\Delta y_{m,t} = \widehat{\epsilon}_{m,t}$. $x_{m,t}$ is seasonally adjusted and linearly detrended local concentration according to eq.9. Source: AWFP.

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Table 5: Instantaneous volatility and concentration of economic activity: robustness checks.

	Dep.var.: $\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}\lvert\widehat{\epsilon}_{m,t}\rvert$		
	Baseline	HP-filtering/baseline concentration	Baseline transformation/Herfindahl
concentration$_m$	-0.001	-0.002***	0.009***
	(-1.36)	(-2.70)	(3.56)
Observations	72	72	72

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Local employment average conditional volatility in city m on average concentration (Proposition 4a). Local employment average conditional volatility corresponds to average instantaneous volatility $\frac{1}{T}\sum_t \sqrt{\frac{\pi}{2}}\lvert\widehat{\epsilon}_{m,t}\rvert$, where $\widehat{\epsilon}_{m,t} = \Delta y_{m,t}$ (column 1 and 3) and $\widehat{\epsilon}_{m,t} = y^{HP}_{m,t}$ (column 2). concentration$_m = \overline{x}_m$ in eq.9 (column 1 and 2) and equal to the exponential of the constant term estimated by running a city-specific regression of the (log of the) Herfindahl index on an intercept and linear trend. Source: AWFP.

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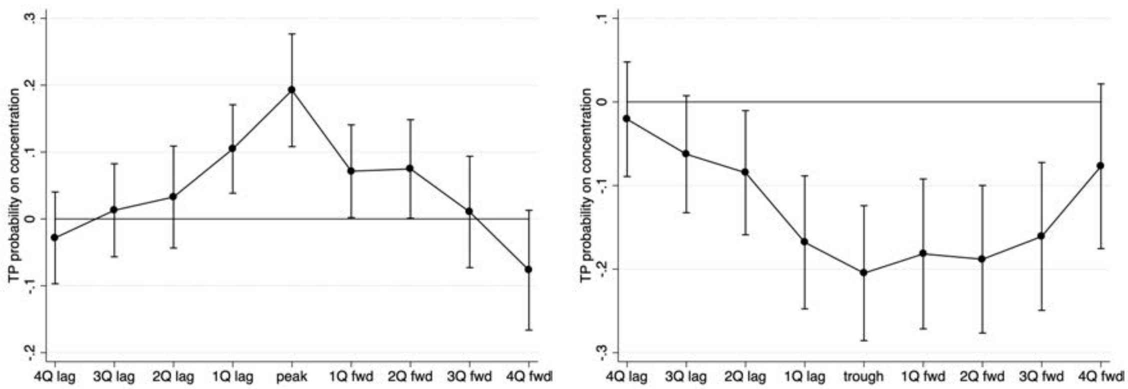
B Figures

Figure 1: Probability of turning point and local concentration.



(a) Peak (b) Trough

On the vertical axis the estimated coefficient of eq.11 is reported for different lags and leads relative to the turning point under consideration together with confidence bands at $\alpha = .90$ significance level (robust standard errors). Source: AWFP.

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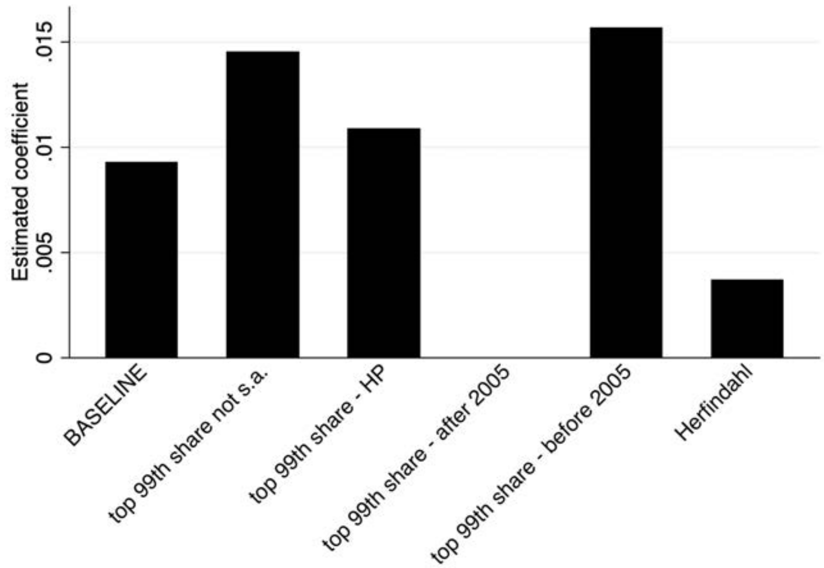
Figure 2: Instantaneous volatility and concentration of economic activity: robustness checks.



On the vertical axis the estimated coefficient of interest, $\widehat{\varphi}$, in eq.10 under alternative assumptions. A missing bar denotes a coefficient not statistically significant at the 90% confidence level. Source: AWFP.

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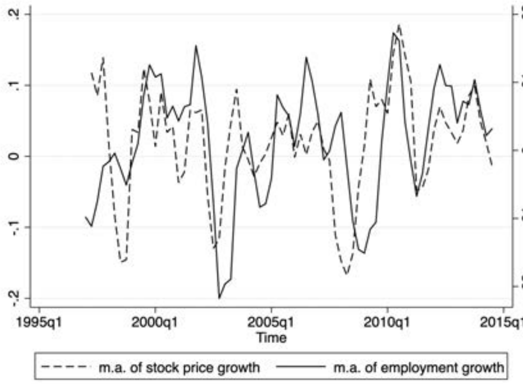
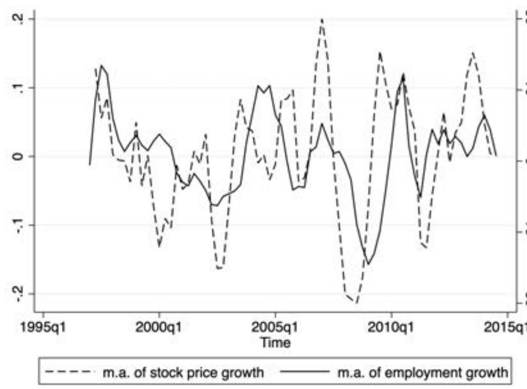
Figure 3: Company stock price growth rate and local employment growth rate.



(a) BMW, Landshut: $\rho = .25$

(b) BMW, Wackersdorf: $\rho = .21$

(c) Beiersdorf, Hamburg: $\rho = .24$



(d) Daimler, Rastatt: $\rho = .32$

Company stock prices are downloaded from Yahoo Finance at the weekly frequency and closing price is used. Stock price growth rate corresponds to the log difference between the price during the first week of a quarter and the price during the first week of the previous quarter. Closing prices are seasonally adjusted and the correlation is calculated on the growth rate. For representation purposes, 3-quarters centred moving averages are reported. Source: AWFP and Yahoo Finance.

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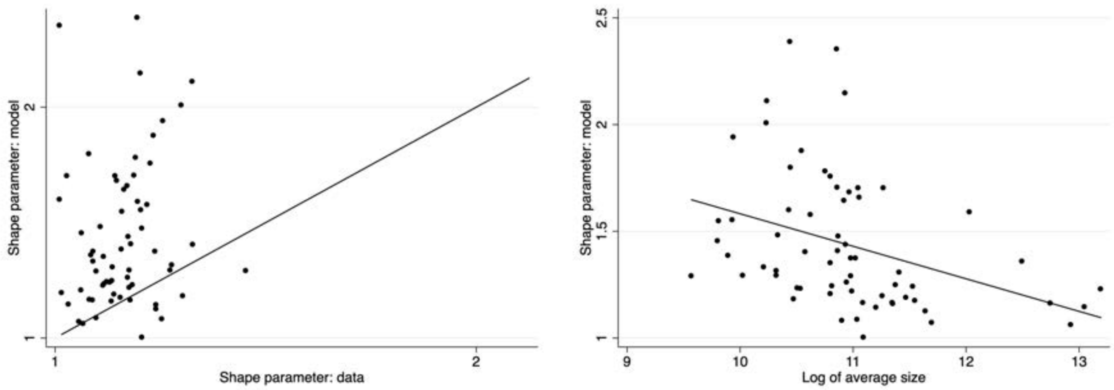
Figure 4: Comparison between shape parameter in the data and in the model and relationship between shape parameter in the model and city size.



Estimates for 64 cities out of 72 in total. In the left hand side graph, the 45 degree line is plotted. In the right hand side graph, a linear fit is plotted.

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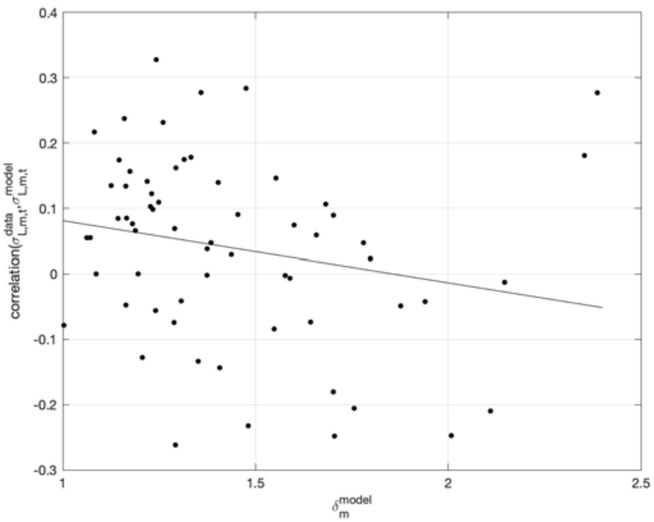
Figure 5: Correlation between volatility in the model and in the data and the estimated shape parameter.



Estimates for 64 cities out of 72 in total.

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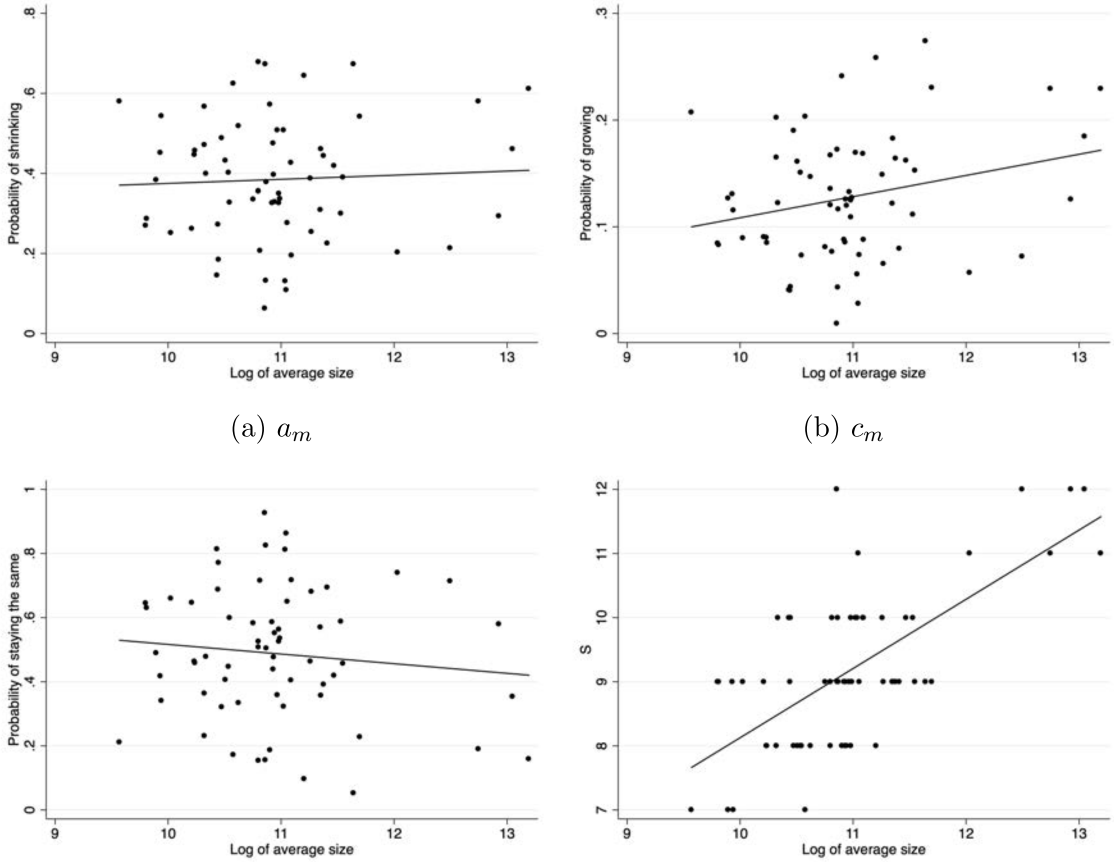
Figure 6: Establishment dynamics and city size.



(a) a_m (b) c_m (c) b_m (d) S_m

Estimates for 64 cities out of 72 in total. Each graph features a linear fit of the data plotted.