The Volatility Advantages of Large Labor Markets*

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Abstract

Firms' labor demand is more volatile in larger cities. We propose and test a novel explanation for this finding. Faster hiring conditions attract productive firms with more volatile activity to denser locations where they can swiftly downsize or expand. We estimate a model of firm location choice using French data and show that (i) firm volatility is half as predictive of location choice as productivity; (ii) both dimensions reinforce each other. This mechanism reduces the productivity–density gradient among volatile firms. Imperfectly correlated firm-level shocks, combined with higher operating costs induced by density, generate matching economies.

JEL-Classification: J23, J63, J64, R12, R23

Keywords: Volatility, Labor market pooling, Firm location, Agglomeration economies

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When I do nothing
I cost less money
Than when I'm working
Or so they tell me.
Bernard Lavilliers, *Les Mains d'Or.*[1]

1 Introduction

The productivity-density nexus is a central tenet of economic geography and urban economics (Combes et al., 2012, Gaubert, 2018). One of the channels through which agglomeration economies operate is the matching channel, whereby high human densities facilitate the speed and quality of the hiring process (Duranton and Puga, 2004). This channel is particularly beneficial for high-productivity firms because their opportunity costs of operating with limited capacity are higher. Therefore, the complementarity between employer productivity and local hiring conditions gives rise to a labor market pooling externality (Bilal, 2023). While heterogeneity in firm productivity is a key component of this mechanism, the literature has largely neglected another dimension of heterogeneity that is also pervasive in the data, namely the *volatility* of firm activity. However, Krugman (1992) already pointed out the potential benefits of labor market pooling for firms with volatile and imperfectly correlated labor demand. Firms affected by positive demand shocks then benefit from neighboring firms downsizing when they try to recruit.

In this paper, we study agglomeration patterns when firms are heterogeneous along two dimensions, productivity and volatility. We do so in the context of a stylized model and in the data. In the model, firms are willing to adjust their employment positively or negatively in response to idiosyncratic demand shocks. High job-filling rates reduce the cost of these fluctuations, more so for high-volatility firms. We investigate how this complementarity between volatility and local hiring conditions interacts with sorting patterns along the productivity dimension when firms can either hold employment constant or choose to adjust to shocks. In the data, we first provide evidence of a systematic correlation between the density of cities and the average volatility of firms there, conditional on productivity. We then estimate models of location choice to quantify the relative importance of productivity and volatility in shaping location choice decisions. The results are in line with the model's predictions and confirm the quantitatively large role of volatility in firms' location choices.

[1]Song by a popular French blue-collar singer. The original lyrics are "Quand je fais plus rien, moi / Je coûte moins cher / Que quand j'travaillais, moi / D'après les experts."

We begin by documenting new evidence on firm productivity, firm volatility, and local (working-age) population density. We use French administrative data at the worker and firm level over the period 2010-2019, identifying (large) cities with (dense) commuting zones. We use the monthly frequency of the data to measure idiosyncratic shocks to a firm's labor demand, and their volatility over time. Our first key finding is that intra-firm employment volatility is higher in denser cities, even after controlling for various relevant firm characteristics such as sector, size, and age. This correlation is quantitatively significant and is hardly reduced when we also control for firm productivity. The second important empirical result is that we find a flatter productivity density gradient among firms with high employment volatility. The elasticity of firms' average productivity with respect to density drops by half when moving from the first to the last decile of the volatility distribution. These reduced-form evidence hint towards an impact of volatility, beyond and above productivity, for the spatial agglomeration of firms.

We propose next a simple search model inspired by Mortensen and Pissarides (1994) to rationalize these facts. Firms in the model differ in their productivity and the volatility of the demand they face. The demand for firm's production alternates between high and low levels, and the variance of sales induced by these cycles is heterogeneous across firms. Firms can mitigate the impact of demand volatility by adopting three different employment strategies. The first one aims at maintaining employment levels even in bad times and is chosen by the most productive firms. In the second, the firm freezes hiring in bad states. Freezing hiring avoids facing operating costs in bad states at the cost of entering good states with vacant positions. In the third one, firms "churn": they adopt a turnover strategy, firing workers when hit by bad shocks and hiring only when their demand is high.[2] The latter strategy is preferred by the most volatile firms (holding productivity fixed) and by the least productive firms (keeping volatility constant), thus allowing low-productivity firms to be active in large cities when they are volatile enough and experience high demand periods.

The model then allows us to analyze where firms choose to locate. The crucial trade-off for firms is that large cities are expensive to operate in — because of higher labor costs or rent — but allow firms to find workers more quickly when they are needed — when firms experience a positive demand shock. Intuitively, locating in a large city provides "insurance" against volatility because larger cities offer lower adjustment costs for firms.

[2] Burgess et al. (2000) introduce "churning" as a concept to describe a phenomenon where firms simultaneously lose and gain workers. In our case, we study firm behavior in a steady-state, where firm size is constant on average across periods. For this reason, we consider our mechanism as an instance of "non-simultaneous churn" and name our third strategy "churning".

This mechanism is particularly beneficial for high-productivity firms, which have the most to gain from being able to hire more quickly. It is also stronger when a large component of volatility is idiosyncratic, as firms that downsize free up workers that can be hired by expanding firms. Therefore, the model predicts that (i) firms sort positively on productivity and volatility into large cities; (ii) these two dimensions reinforce each other; and (iii) the resulting gradient of firm productivity with city density decreases with firm volatility. Since firms are more likely to churn - and thus ease the hiring conditions on the labor market for other firms — when they face higher operating costs, this model provides a microfoundation for matching economies based on the existence of urban costs.

Motivated by our theoretical results, we then turn back to our data and illustrate the main predictions of the model. To that end, we propose two distinct proxies to measure the exogenous component of a firm's employment volatility, based on different assumptions, which can be constructed on two distinct sets of firms. Both are akin to a shift-share, using exposure to demand shocks at the firm level combined with global demand variations. The first one combines information on the firm's product portfolio with the time series of international demand at the product level adapting the approach of Hummels et al. (2014). Intuitively, the exogenous component of volatility is driven by firms specializing in products for which demand is more or less volatile. We measure the expected volatility of demand resulting from a firm's decision to produce a given portfolio of products, which we assume is exogenous to its location choice. In the second proxy, we measure the volatility of demand using input-output linkages. In this case, firm-level demand is driven by downstream firms at the disaggregated sectoral level, and global demand, measured from monthly time series of the combined sales of French firms in a given sector. In that case, we assume that a firm's decision to enter a given sector, which has consequences for the potential volatility of its downward partners, is exogenous to its location choice.

Using a local projection method, we first confirm that the recovered demand shocks, either at the product or at the sector level, do trigger firm-level labor demand adjustments. Both measures yield similar response functions. The effect, albeit small, is statistically significant after two months and increases for several months after the shock, before plateauing after six months. In addition, employment responses following demand shocks are faster and larger for firms located in denser locations. We use these two shocks to construct two measures of expected demand volatility at the firm level. We then estimate a model of firm location choice based on all firm creation events observed in our dataset. The estimation results are similar in both samples and confirm that more volatile firms are more likely to locate in denser commuting zones. Quantitatively, firm demand volatility is half as predictive of firm location choice as firm productivity. Consistently with our modeling assumptions, our estimates also show that volatility and productivity are complementary in firm location choice: more productive firms are more likely to be created in larger cities if they are also more volatile. This differential sorting pattern contributes to explaining why the productivity-density gradient is flatter for volatile firms.

Anecdotal evidence — The labor market externalities that we study are important when firms experience volatile labor demand and labor demand shocks have a large idiosyncratic component. A well-known example is the advertising industry, which is concentrated in global cities such as Paris, London and New York. Constant idiosyncratic demand fluctuations due to winning or losing large contracts generate labor reallocation between winners and losers, including both large and small firms.

While, in this first example, workers are very specialized and firms often are direct competitors, we argue in this paper that a more general argument can be made about the impact of density on the clustering of firms with imperfectly correlated labor demand. Anecdotal evidence is fairly easy to find in the French press for large firms. In November 2009, STX shipyards in Saint-Nazaire announced that an additional 14% of its labor force had agreed to voluntarily quit after the company had obtained no new orders since 2007, having already shed thousands of jobs in a short time span. However, the local economy was much more diversified than during the previous major layoff in 1988, and some other local firms were experiencing growth: the Airbus plant was launching a new aircraft model, Acmat had obtained orders for military vehicles abroad, Man Diesel's engine sales were increasing, and Elengy was expanding a major liquified natural gas terminal. This enabled some workers released from STX and its subcontractors to be absorbed by firms experiencing strong demand. When the shipyards started rehiring in September 2013 as orders for huge cruise ships increased, they were able to draw on a rich local labor market, including their own past subcontractors that went bankrupt (Baudet, Atelier du Marais, SMH) or firms such as Elengy (or its subcontractors) that finished its terminal expansion.[3]

Similar patterns can also be observed across firms of different sizes. For example, in Béthune,

[3]See "A Saint-Nazaire, la navale décline mais la relève est là", in *L'Usine Nouvelle*, 10/10/2010; "Chantiers navals STX de Saint-Nazaire : cinq ans de hauts et de bas", in *Le Figaro*, 5/5/2013; "Mise en liquidation des chantiers Baudet de Saint-Nazaire (67 salariés)" in *Marine & Oceans*, 08/8/2013;"STX France recrute pour préparer l'avenir" in *L'Usine Nouvelle*, 16/9/2013; "Elengy terminal renovation nears completion" in *LNG Industry*, 28/10/2013; "Le parisien Maleville sauve les Ateliers du Marais" in *L'Usine Nouvelle*, 17/1/2014; "Le groupe nazarien Sofreba en difficulté" in *L'Usine Nouvelle*, 9/10/2014.

recent large plant closures have benefited several dozen of smaller firms in manufacturing, logistics and services that used this opportunity to expand their operations, with local unemployment agencies helping with (limited) retraining needs.[4] In our data, Saint-Nazaire and Béthune belong to the 84% and 93% percentiles of the distribution of the working-age population density by commuting zone, respectively. Conversely, large positive demand shocks for products of firms located in smaller local labor markets may often cause them to forego the pursuit of profitable opportunities or engage in costly hiring campaigns, as is often documented in the local press and, more and more, in local policy briefs from the National Statistical Institute.[5]

Relationship to the literature — Many studies provide theory and evidence that more productive firms sort into larger cities (Combes, 2000, Gaubert, 2018, Lindenlaub et al., 2022). Our work presents a new mechanism for agglomeration economies based on the combination of firm productivity and volatility: matching economies arise endogenously from firms' hiring and firing decisions when they face more expensive operating costs. This mechanism may also help explain why relatively unproductive firms can survive in denser areas (Combes et al., 2012), in addition to the mechanisms already proposed in the literature.[6] A complementary mechanism that is also consistent with our argument, even in the absence of productivity differences, is labor market pooling: if demand volatility is uncorrelated across firms, there is a clear advantage for firms to agglomerate because they can hire more workers in good times. This source of agglomeration economies, already recognized by Marshall, was popularized by Krugman (1992). However, this argument has remained largely ignored by the empirical literature.

To the best of our knowledge, the main existing attempt to provide reduced-form evidence for this channel is the study by Overman and Puga (2010). In their static model, firms do not know their productivity before entering a market: productivity is affected by an idiosyncratic shock with known variance. Firms' profits are convex to this shock because firms hire more when the shock is positive, and expected profits thus increase with the variance of the shock. Yet, since wages rise with local demand, firms with higher variance will be all the more profitable when there are many firms, to counteract the effect of individual positive shocks

[4] See "Dans le Béthunois, des bonnes nouvelles à la chaîne", in *Libération*, 10/25/2023.

[5] See, e.g., "Les difficultés de recrutement s'accentuent davantage dans certains territoires" in *Insee Flash Pays de la Loire*, 3/21/2024.

[6] Another mechanism, also based on firm entry, is that higher entry costs in larger cities shield unproductive firms from competition from other firms if entry is decided before productivity is realized (Melitz, 2003, Heise and Porzio, 2023).

on the local wage level.[7] Therefore, the model predicts that groups of firms with more variability in labor demand will be more agglomerated, a prediction borne on sector-level data. We instead test our model on individual data and explore the interaction between productivity and volatility on sorting patterns.

By focusing on hiring frictions, this paper also contributes to the literature on the relationship between city size and unemployment. While current leading models of spatial labor markets (Bilal, 2023, Kuhn et al., 2021) posit that more productive firms select into more productive locations, resulting in a negative correlation between average firm productivity and local unemployment rates, they do not directly relate these observations to city size. In the data, large cities are characterized by a higher share of high-productivity firms, but they do not necessarily have lower unemployment rates. One reason for this could be that the mobility of unemployed workers acts as a balancing force in the spatial equilibrium (Gaigne and Sanch-Maritan, 2019). However, churning strategies of firms provide an alternative explanation: if firms in large labor markets have higher structural volatility and consequently higher employment volatility, there may be more aggregate labor turnover and also more unemployment. This mechanism would mitigate the effect of the agglomeration of more productive firms in larger cities.

More generally, this paper complements the literature on the spatial dimension of matching in cities, which has so far largely focused on the worker side (Gan and Zhang, 2006, Bleakley and Lin, 2012, Schmutz and Sidibé, 2019, Dauth et al., 2022, Papageorgiou, 2022, Moretti and Yi, 2024) with some incomplete evidence on firms (Glaeser et al., 1992, Henderson et al., 1995, Combes, 2000, Duranton, 2007, Findeisen and Südekum, 2008). In contrast to recent work on the worker side, we abstract from worker heterogeneity. Therefore, we do not address the impact of city size on the level of match assortativeness and we focus on hiring speed as the sole determinant of agglomeration economies.[8] Moreover, in contrast to the existing literature on the firm side, we do not consider structural characteristics of the economy, such as sectoral composition. Instead, we focus on the heterogeneity of firms, conditional on the sector in which the firm operates. We incorporate two dimensions of heterogeneity that

[7] Contrary to our setting, firms do not face hiring frictions. In this respect, we are closer in spirit to the seminal model of Helsley and Strange (1990), which derives agglomeration economies from the matching process of workers to firms.

[8] We also abstract from the decision of workers to quit their jobs, which is not observed in our data. Using survey data on U.S. firms, Weingarden (2020) estimates that at least one-third of firm churning is actually initiated by the employer through layoffs. This figure is arguably a lower bound, since employers may have a financial incentive to get workers to quit rather than lay them off. Weingarden (2020) shows that this component of churning is acyclical, unlike worker quits, which fits well with our modeling assumption of firm-specific shocks.

affect the first and second moments of firms' labor demand. In doing so, we draw inspiration from the macroeconomic literature, which has long discussed heterogeneity across firms in productivity *and* volatility.[9] We enrich this literature by introducing novel, firm-specific shifters of employment volatility. Finally, we enrich the literature on labor market churning (Burgess et al., 2000, Nekoei and Weber, 2020, Weingarden, 2020) with a focus on the spatial dimension.[10]

The remainder of the paper is organized as follows: in Section 2, we provide descriptive evidence that employment volatility increases with city size and that the productivity gradient with respect to city size decreases with employment volatility; in Section 3, we present a simple model of firm decisions where employment volatility and location choice are jointly determined. The model predicts that firms sort across space based on the volatility of their activity, and we formally test this prediction in Section 4. Section 5 concludes.

2 Motivating facts on firms' spatial patterns

2.1 Data

Sample selection — The empirical analysis exploits matched employer-employee data for France over the period from 2010 to 2019 (DADS Postes). This data allows us to characterize the level and volatility of a firm's labor demand, at the monthly level.[11] For each employer-employee relationship, we know the type of contract (permanent or short-term), the number of hours and associated earnings, and the worker's occupation. On the employer's side, we know the location of each establishment, as well as the sector of activity and date of creation. Finally, the data can be matched with two additional yearly firm-level datasets, namely balance-sheet data used to estimate productivity (FARE) and a production survey (EAP) that provides additional information on the firm's portfolio of products.[12]

[9] Comin and Philippon (2006) and Comin and Mulani (2006) document the rise in firm-level volatility among publicly traded US firms in the second half of the 20th century. Davis et al. (2007) instead show diverging trends between public and private firms. In this literature, firm volatility is explained by a combination of aggregate shocks and firm idiosyncratic fluctuations. di Giovanni et al. (2014) provide evidence that a large component of individual firm volatility is driven by idiosyncratic shocks that reflect a combination of demand and supply-side factors.

[10] Note that our results also echo some results in the trade literature such as Cuñat and Melitz (2012) showing that countries with more flexible labor markets specialize in sectors with higher volatility.

[11] In the rest of the paper, we use a measure of employment equal to the full-time equivalent, based on the number of days worked in each month. We define full-time workers as employees who work 30 days in each month.

[12] The EAP survey is exhaustive for firms in the manufacturing sector above a size threshold of 20 employees and with sales of minimum 5M€. Merging the employer-employee linked data with the this survey

The analysis focuses on firms in manufacturing, construction, and services.[13] We use the address of each establishment to assign it to a commuting zone. Our sample includes plants in mainland France, which is divided into 280 commuting zones ("zones d'emploi"), covering the entire territory. Since the focus is on how firms locate across local labor markets, we aggregate plant-level information at the level of a commuting zone, i.e., firms with multiple plants in the same commuting zone are treated as a single plant. In the main analysis, we focus on the January 2015 cross-section of the data, which corresponds to the midpoint of our period, but other reference points yield similar results. We focus on firms located in a single commuting zone because some key variables for our analysis (productivity and demand volatility) can only be calculated at the firm level due to data availability, and we restrict the sample to firms with at least two employees. This leaves us with 316,041 firms with non-missing data on the key variables of interest (productivity, employment volatility, 2-digit industry, firm age, and firm size). Table A.1 in the appendix details the sample selection process.

Table 1: Population density and firms by commuting zone

	Density	Number of firms
Mean	150.75	1,129
Std. Dev.	496.48	3,193
25th percentile	39.74	391
50th percentile	68.69	595
75th percentile	122.32	1,032

Notes: Summary statistics over the distribution of the 280 commuting zones in mainland France. Density is measured by working age population (measured from the Census) divided by the commuting zone's area in squared kilometers, for the year 2015. The number of firms is the total number of firms used in our analysis of the January 2015 cross-section, per commuting zone.

Density — Each commuting zone is characterized by its population density, which is defined as the size of its working-age population divided by its area (in square kilometers). The working-age population is taken from the Census, where the breakdown of the population by age and municipality is available at a 5-year frequency. For years in which the population is not available, we use data from the previous non-missing year. The area of commuting zones

introduces severe censoring. The stylized facts discussed in this section exploit the full sample and we restrict the analysis to firms in the EAP survey to build one of our two exogenous measures of volatility, in Section 4.1.

[13] We exclude the public sector, agriculture, forestry, and fishing, finance and insurance, energy and waste production and distribution, artistic activities, overseas activities, and household services.

is based on INSEE 2020 shapefiles (Base des zones d'emploi). Table 1 provides statistics on the distribution of commuting zones and the number of firms in each location for the January 2015 cross-section.

Productivity — Firms differ in size, which is typically explained in the literature by some randomness in firm productivity. In the data, we estimate firms' total factor productivity $\phi_{f,t}$ using the Levinshon-Petrin estimation technique with the Ackerberg et al. (2015) correction. Productivity is estimated as the residual of a production function equation including capital and three types of labor distinguished by their skill levels (Combes et al., 2012). Details of the estimation are provided in the Appendix A.3.

Employment volatility — In our model, firms are also heterogeneous in terms of the volatility of their labor demand, due to a combination of structural factors and their endogenous workforce management decisions. We use the panel dimension of the dataset to characterize the volatility of a firm's labor demand. Following Davis et al. (2006), we define a firm's volatility as:

$$\sigma_{f,t} = \sqrt{\frac{1}{2\omega+1}\sum_{\tau=-\omega}^{\omega}(\gamma_{f,t+\tau} - \bar{\gamma}_{f,t})^2} \tag{1}$$

where $\gamma_{f,t}$ is the year-on-year monthly growth rate of labor demand and $\bar{\gamma}_{f,t}$ is the mean growth rate computed over the $(2\omega + 1)$-month period centered around date t. Our baseline measure uses a 35-month window, centered around January 2015. The variable is constructed using the total number of full-time equivalent employees as our measure of labor demand. This measure of employment volatility captures second moments in the time-series of labor demand at firm-level, thus treating symmetrically upward and downward adjustments.

As our focus is on the potential sources of labor market pooling, which occurs when hiring firms can benefit from other firms downsizing at the same time, we further restrict our attention to *idiosyncratic* sources of employment volatility. To this aim, we systematically residualize the growth rate of employment $\gamma_{f,t}$ in the sector×month×year dimensions.[14] The sector×month×year fixed effects absorb any component in labor demand growth rates that

[14] Monthly growth rates of labor demand are winsorized at the 1st and 99th percentile within each of 5 firm size classes. These 5 firm size classes identify firms between 2 and 9 employees, between 10 and 49 employees, between 50 and 249 employees, between 250 and 4,999 employees, and plants of 5,000 and above employees.

is common across firms from the same sector. This notably includes business cycle shocks, be they aggregate or sector-specific. Instead, the residual captures shocks that are idiosyncratic to the firm. Following the macroeconomic literature (e.g. Gabaix, 2011, di Giovanni et al., 2014), we interpret the standard deviation of the residual as a measure of idiosyncratic volatility. As shown in Appendix Table B.1, the vast majority of firm-level dispersion in volatility is driven by idiosyncratic shocks.

In Appendix tables B.2 and B.3, we compare our baseline measure with alternatives capturing slightly different aspects of the firm's employment volatility. While the baseline measure relies on employment, and thus on adjustments at the extensive margin, we show that the correlation with the volatility of hours is high, at .85. Pure intensive margin adjustments, through the number of hours per employee, are not the main factor at the root of a firm's labor demand fluctuations. Likewise, one may be concerned that certain type of contracts, most notably short-term contracts, are particularly well-suited to help the firm smooth out the impact of fluctuations in demand. The correlation of our baseline measure with a measure of volatility recovered solely from the growth of open-ended contracts (CDI contracts — "Contrat de travail à durée indéterminée") is however high, at .75. The volatility of permanent contracts is still substantial, only 5% lower than the volatility of overall employment at the sample mean. Finally, our baseline volatility measure correlates highly with alternatives using slightly different strategies for identifying the idiosyncratic component of volatility. The most sensitive robustness check is obtained from statistics computed on month-on-month, instead of year-on-year, growth rates. Mechanically, the average volatility recovered from month-on-month growth rates is an order of magnitude smaller. However, its cross-sectional correlation with the baseline is still high at .70. In our baseline, we neglect month-on-month fluctuations that may to a large extent come from a sector-specific seasonality.

Descriptive statistics — Table 2 contains descriptive statistics on the baseline sample of firms. In January 2015, the sample is composed of 316,041 firms that we observe over at least 35 consecutive months. As expected, firms display significant heterogeneity in size, employment volatility, and productivity. Appendix Figure B.1 shows that, conditional on its size, the median firm with 2-10 employees adjusts its labor demand (up or down) by approximately 0.8 employees per month, on average.

Table 3 shows how our measure of employment volatility correlates with important covariates. Here, we systematically control for firm size class fixed effects for consistency with the rest of the analysis. Firm size is negatively correlated with employment volatility. First, as seen in

Table 2: Distribution of employment volatility and productivity

	Size	$\log\sigma$	$\log\phi$
Mean	11.52	-1.94	3.16
Std. Dev.	22.04	0.96	0.70
25th percentile	3.00	-2.37	2.79
50th percentile	5.87	-1.85	3.18
75th percentile	11.00	-1.35	3.57

Notes: The variables are calculated for the January 2015 cross section of the dataset ($N = 316,041$). Size is the number of employees. Productivity is based on 2015 balance-sheet data. Idiosyncratic volatility is computed using a 35-month window centered around January 2015 and the formula in equation (1), where labor demand year-on-year growth is residualized in the sector×month×year dimensions.

Table 3: Firm employment volatility: correlates

	Dep. Var: log Employment volatility				
	(1)	(2)	(3)	(4)	(5)
log Age	-0.332	-0.336	-0.313	-0.182	-0.179
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log Productivity		-0.069	-0.056	-0.076	-0.064
		(0.003)	(0.003)	(0.003)	(0.003)
% low-skilled workers					0.162
					(0.006)
Size class FE	✓	✓	✓	✓	✓
Sector FE			✓	✓	✓
Average growth				✓	✓
Adjusted R2	0.117	0.119	0.139	0.269	0.270

Notes: the table shows the conditional correlation between our baseline measure of idiosyncratic employment volatility (where labor demand year-on-year growth is residualized in the sector×month×year dimensions) and the firm's age, productivity, and share of low-skilled workers measured in hours. The estimates are based on the sample of 316,041 firms in January 2015. The table contains OLS coefficients and their estimated robust standard errors in parentheses.

column (1), older firms are less volatile, which is a standard pattern in firm-level data (Davis et al., 2007). This relationship can reflect a form of internal diversification of risks when firms age and grow. Appendix Figure B.2 illustrates this pattern in more detail, showing that most of the age variation takes place within the first four years of a firm's life cycle, while volatility stabilizes afterwards.

Second, more productive firms are also less volatile (column 2). This empirical correlation is then taken into account and we systematically examine the effect of a firm's volatility, *conditional on its productivity.* Controlling for sector fixed effects (column 3) does not significantly increase the explanatory power of the model once the other controls are included. This is consistent with firms displaying heterogeneous volatilities, including within the same sector. In column (4), we further control for the average firm growth over the 35 consecutive periods used in the calculation of employment volatility, corresponding to $\bar{\gamma}$ in eq. (1). This increases the explanatory power of the model, but does not affect the direction of the other effects described in the previous columns.[15] In column (5), we control for the share of low-skilled workers, who, on average, make up 29% of firm employment in our sample (see Section A.2 in the Appendix for further details). Employment volatility is positively correlated with this share, consistent with the intuition that low-skilled workers, who work in more generic occupations, are more subject to workforce adjustments.

2.2 Motivating stylized facts

The productivity-density gradient — The literature in economic geography has long discussed agglomeration patterns of firms over space. We first reproduce the evidence focusing on the productivity-density correlation (Combes et al., 2012). More precisely, we run the following regression based on the cross-section of firms observed in January 2015:

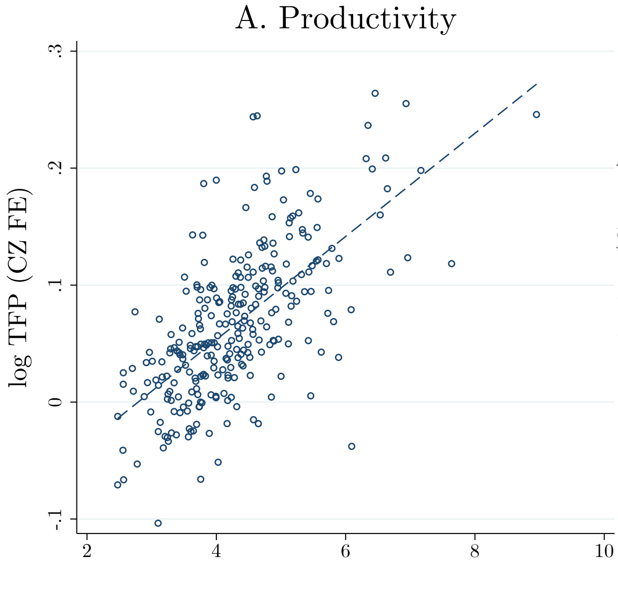
$$\log \phi_f = X_f \beta + FE_{M(f)} + \varepsilon_f \tag{2}$$

where X_f is a set of controls and $FE_{M(f)}$ denotes a set of fixed effects for each commuting zone. In this equation, the fixed effect captures the average productivity of firms in any commuting zone, once controlling for the heterogeneity that correlates with the control variables, namely the firm's 2-digit sector of activity, its size class, and age.

Panel A of Figure 1 illustrates the correlation between the conditional average productivity of firms and the population density of the commuting zone. As expected, the correlation is positive and significant, consistent with the view that dense commuting zones attract more productive firms, on average. As mentioned in the introduction, there is a vast literature explaining the correlation using various theoretical frameworks. A strand of the literature notably points to the role of matching economies through pooling externalities: Locations

[15] Figure B.3 in the Appendix shows that the distribution of month-on-month employment volatility does not change dramatically when comparing firms that have different patterns of employment monthly growth. Firms with mostly zero growth (more than 90% zero monthly growth rate over the 35-month interval around January 2015) display an employment volatility distribution that is slightly more shifted to lower levels, while the remaining groups display comparable employment volatility distributions.

Figure 1: The productivity and volatility advantage of large cities

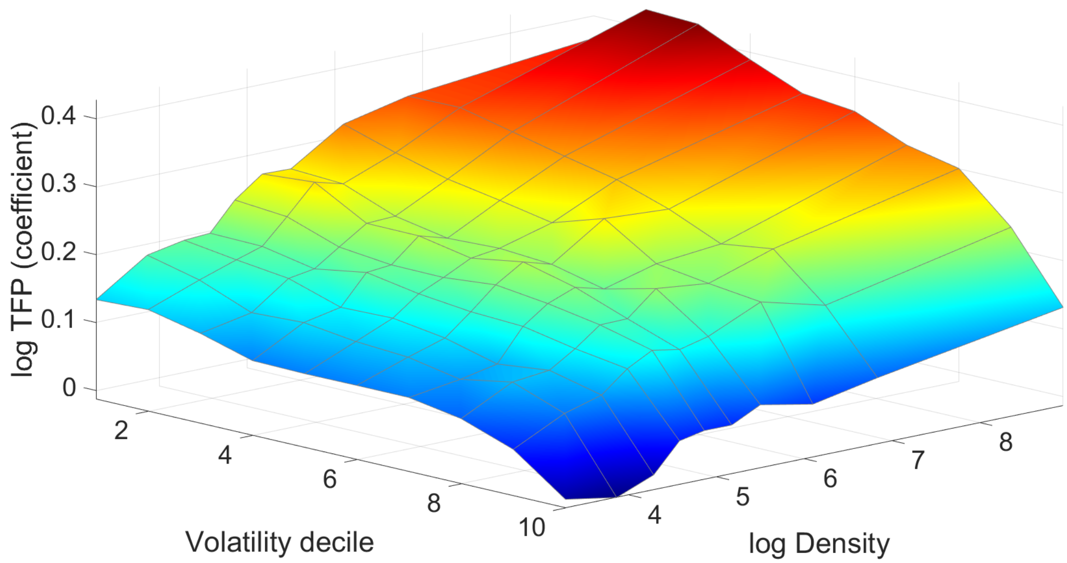


Notes: Panel A shows the correlation between the mean productivity of firms and the density of the commuting zone where firms locate. Mean productivity is based on 2015 balance-sheet data. The correlation is conditional on the following firm characteristics: sector, size class, age, average growth during the period over which employment volatility is computed ($\bar{\gamma}$). The slope is 0.044 (the adjusted R^2 is 0.4326) and the slope is significantly different from 0 at 1%. Panel B shows the correlation between the mean volatility of firms and the density of the commuting zone where they locate. Idiosyncratic volatility is measured by the standard deviation of the firm's labor demand year-on-year growth, residualized in the sector×month×year dimensions. Mean volatility is based on the January 2015 cross section of firms and is conditional on the following firm characteristics: sector, size class, firm age, firm average growth ($\bar{\gamma}$), log productivity. The slope is 0.026 (the adjusted R^2 is 0.1053) and the slope is significantly different from 0 at 1%.

with higher meeting rates are most beneficial to high-productivity firms that are able to hire more quickly (Bilal, 2023). To the extent that pooling externalities are part of the story, we shall expect that the benefit is also larger for more volatile firms, conditional on productivity. As shown in Section 2.1, firms are indeed strongly heterogeneous in terms of the volatility of their labor demand, which may thus affect spatial location patterns.

The volatility-density gradient — We provide preliminary evidence for a role of employment volatility in Panel B of Figure 1. As in Panel A for productivity, we first recover here an estimate of firms' average employment volatility at the commuting zone level. We run a regression similar to eq. (2), using the log of employment volatility as the LHS variable and controlling for log of productivity. We then correlate this measure for conditional average employment volatility with the density of the commuting zone. Here as well, the conditional correlation is positive and significant, consistent with the intuition that pooling externalities are particularly valuable for volatile firms, which may then agglomerate in

Figure 2: The productivity-density gradient, along the volatility distribution



Notes: The figure shows the conditional correlation between log productivity of firms and the log density of the commuting zone where they locate by firms' employment volatility decile. Productivity is conditional on the following firm characteristics: sector, size class, firm age and average firm employment growth. The estimated equation includes the interaction between the decile of density of the commuting zone where the firm is located and the decile of idiosyncratic employment volatility, with the reference category set to the tenth decile of volatility and the lowest density bin. All the coefficients associated with the different productivity-density cells are are statistically significant at conventional levels, except the two coefficients associated with the tenth decile of volatility and the second and third deciles of density. Idiosyncratic volatility is constructed as the standard deviation of the firm's labor demand growth, residualized in the sector×month×year dimensions. Data is based on the January 2015 cross section of firms.

denser commuting zones.[16]

The productivity-density gradient by volatility — Finally, Figure 2 provides a third motivating stylized fact that directly tackles the joint correlation between density, employment volatility, and productivity. Instead of recovering the correlation between firms' attributes and the density of the firm's commuting zone in two stages, we now directly introduce density in eq. (2). The downside is that we can no longer control for unobserved heterogeneity between commuting zones using fixed effects. However, we can now inter-

[16]We highlight three outlier commuting zones located in the mountains (Briançon, la Tarentaise, La Maurienne) that display high employment volatility despite their low density. Digging into the origin of the high volatility, we noticed that all three commuting zones are specialized in hospitality sectors (NACE 55 and 56) with firms in these sectors being more volatile than the average firm in the corresponding commuting zones. We suspect that the high volatility is driven by the seasonality of activities in these sectors, which our statistical model with sector×time fixed effects is not able to absorb due to differences in the seasonality of demand in the Alps compared to the rest of France.

act density bins with a measure of the firm's employment volatility to estimate how the productivity-density correlation varies depending on the firm's volatility. Figure 2 illustrates the results in three dimensions: For each decile of volatility and average levels of density within density deciles, the figure reports the conditional average TFP estimated with this regression. While the most volatile firms are less productive than the least volatile ones on average, the difference remains low in commuting zones that belong to the bottom decile of the density distribution (13% between the top and bottom deciles of volatility, see Figure B.4 for a 2D version of Figure 2 in the volatility-productivity plane). Conversely, since the tendency of high-productivity firms to agglomerate in dense cities is less pronounced within the set of more volatile firms, this gap is much higher in the densest commuting zones (23% between the top and first deciles of volatility in Paris, the densest commuting zone in France). Our model in Section 3.3 will rationalize this negative relationship between firm volatility and the productivity-density gradient through the complementarity of volatility and productivity in location choices. See also Figure C.3 for a pattern from our simulated model corresponding to Figure 2.

2.3 The benefits and costs of density

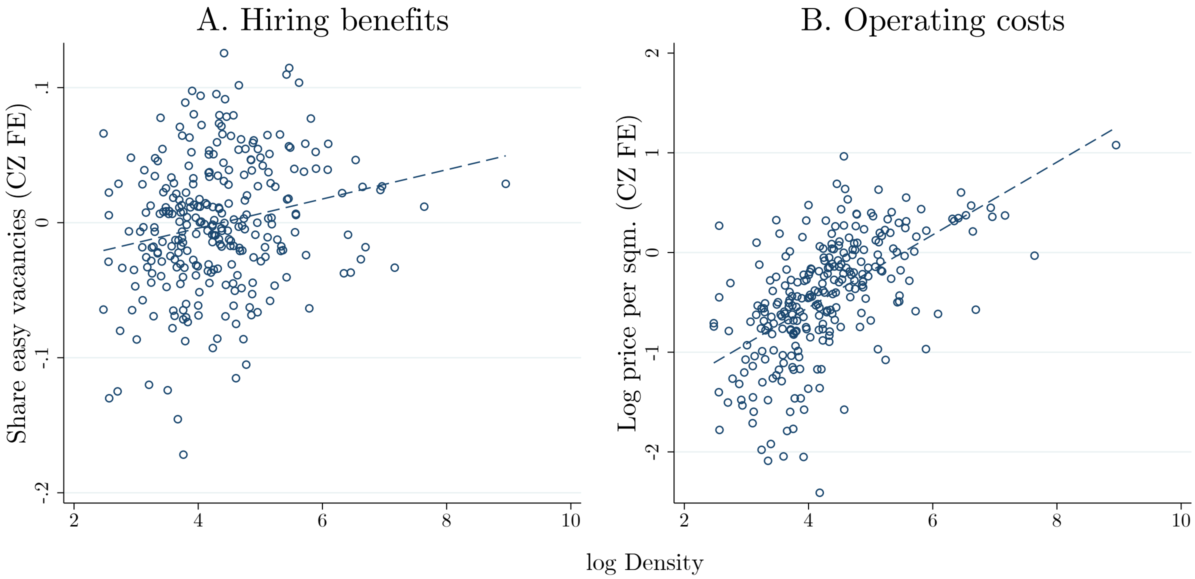
Before presenting the model, we briefly discuss the two dimensions of spatial heterogeneity that will play a role in our theoretical framework, namely that hiring is easier in denser locations, but operating costs are also higher.

Hiring is easier in denser areas — We use the 2015 *Besoins en Main d'Œuvre* survey to document how firms' expectations regarding hiring difficulties vary across space.[17] In this large annual survey, firms declare the overall number of vacancies that they intend to post during the year, including the number of seasonal jobs and the number of vacancies that they expect will be difficult to fill. The data is available at job type-by-location level.[18] We run a regression similar to eq. (2), using the share of vacancies that firms expect to fill easily as the LHS variable. The regression also controls for job type and CZ fixed effects, as well as the total number of vacancies and the share of seasonal vacancies in the job-by-CZ cell.

[17]See Le Barbanchon et al. (2023) for details on other possible sources. Compared to other measures, the survey best fits the assumptions of our model. In particular, our measure reflects firms' *expectations* about hiring difficulties, which are likely to matter when they decide on a location. The 2015 BMO survey was sent to over 1.5M firms or establishments and was answered by over 400K of them. It is weighted by establishment size to obtain representative statistics at the local level.

[18]Earlier vintages have to be destroyed by law and the individual data is therefore not accessible. There are 199 different job types. The smallest level of spatial aggregation available is the *Bassin d'Emploi*, which is slightly smaller than the CZ. When borders do not match, we reconstruct a CZ-level dataset by apportionment using municipal population. The final dataset has 41,774 job type-by-CZ cells.

Figure 3: The benefits and costs of large cities



Notes: Panel A shows the correlation between the mean share of easy-to-fill vacancies and the density of the commuting zone where these vacancies are posted. This variable is based on the 2015 BMO survey and is conditional on the number of vacancies, the share of seasonal vacancies posted for a given job type in a given CZ, and job type fixed effects. The slope is 0.011 (the adjusted R^2 is 0. 0.0416), significantly different from zero at 1%. Panel B shows the correlation between the log rent per squared meter of commercial properties and the density of the commuting zone. This variable is based on the 2015 DVF dataset restricted to sales that concerned commercial properties and is conditional on the log area of the property, the log size of the lot if any (and a dummy variable that indicates so), the number of buildings and the month of the sale. The slope is 0.365 (the adjusted R^2 is 0.3322) and the slope is significantly different from 0 at 1%.

We then correlate the CZ fixed effect with the density of the commuting zone.

Panel A of Figure 3 shows that the correlation is positive and significant, consistent with the fact that firms expect to have less difficulty hiring when they are located in denser CZ. In Appendix B.2, we confirm the robustness of this pattern to many confounding factors. First, we show that the correlation is robust to adding other controls at the CZ level. Second, we use the 2023 firm-level data and show that the correlation is robust to controlling for many establishment-level characteristics in the first stage. Strikingly, it is robust to controlling for firm fixed effects in the sample of multi-establishment firms located across several CZs. We also tried with an alternative measure of labor market tightness, namely the ratio of unemployed workers over vacancies and also found a positive correlation with density. Finally, we note that this correlation may understate the true impact of density on hiring difficulties if the most vulnerable firms to hiring difficulties endogenously select dense locations to overcome those difficulties.

Operating costs are higher in denser areas — It is widely known that larger cities are more expensive for workers to live and firms to operate (Combes et al., 2019). A prominent reason is real estate, as rents are higher in large cities. We confirm this correlation in the data, using average prices on commercial property transactions as a proxy. The source of the data is the 2015 DVF dataset, which records all sales on the French real estate market. We restrict the sample to sales of commercial properties (N=26,860) and regress the log transaction price per squared meter as a function of the log size of the property, the log size of the lot if any, dummy variables for the number of buildings in the property, a month of transaction dummy to account for seasonality and CZ fixed effects. We then correlate the CZ fixed effects with the density of the commuting zone. Panel B of Figure 3 confirms the very strong positive relationship between commercial real estate prices and density.

Worker sorting — Beyond operating costs and hiring difficulties, other CZ characteristics are correlated with density: in particular, larger cities have more skilled workers (Combes et al., 2008, Moretti, 2011). For example, in our data, the slope of the bivariate regression of the share of college graduates among residents on log CZ density is equal to 4%, with an adjusted R-squared of 37%. However, controlling for this share does not affect the correlation with density shown in Figure 1, which suggests that the role of density in the sorting of firms into denser locations along the productivity and volatility dimensions extends beyond and above the skill-density nexus that the literature before us has documented.

While the distribution of workers' skills is indeed quite unequal across space, our baseline model will abstract from this dimension. Taking worker heterogeneity into account could mean that matching differences across space are not solely determined by hiring speed, but also, by match quality.[19] As discussed in Section 3.4, if better matches are created in larger cities, this might mitigate the positive correlation between employment volatility and density, because firms may have an incentive to keep their good matches in bad times. However, we believe that this phenomenon is not of primary importance in our setting. As shown in Table 3, and consistently with intuition, firms with a higher employment volatility also have a higher share of low-skilled workers, who can more easily be replaced, and for whom match-specific productivity is likely to be quite low.

Overall, the evidence in this section confirms that denser cities, which are more expensive to operate in but allow for faster hiring, attract a pool of firms that are systematically

[19] For example, in case of production complementarities between firms and workers, more efficient matches should yield a higher positive correlation between employers' and employees' productivity in larger cities (Dauth et al., 2022, Schmutz-Bloch and Sidibé, 2024).

different from the rest of the population in terms of their productivity but also the volatility of their labor demand. In the next section, we build a model that helps understand these agglomeration patterns.

3 Volatility and firm location: theory

We lay out a simple model of the impact of volatility on firms' location decisions. The model provides a micro-foundation of employment volatility based on firms' hiring and firing decisions and helps understand the trade-offs associated with firms' location choice: in particular, it shows why some firms may prefer locating in a denser city, even if that means operating under higher operating costs. The model's main prediction reads as follows: if firms sort across space based on their structural volatility because hiring is faster in denser cities, employment volatility will increase with density and the productivity-density gradient will be lower for firms with higher volatility. Detailed equations and proofs are provided in Appendix C.

3.1 Framework

We consider a simplified version of the canonical search-and-matching model proposed by Mortensen and Pissarides (1994), where single-job, risk-neutral, profit-maximizing firms face demand shocks and hiring frictions. The economy operates at a steady state and time is continuous. We focus on a partial equilibrium, leaving the worker problem aside. In particular, workers are homogeneous, their location is fixed, they do not search when employed and they do not bargain over wages. We also make the simplifying assumption that firms cannot adjust their labor demand at the intensive margin, by paying overtime or using part-time contracts. As discussed in Section 2.1, the extensive margin is a quantitatively important source of volatility at firm-level.

Set-up — Firms are heterogeneous in terms of their mean productivity $\phi > 0$ and their volatility $\varepsilon \in [0, 1]$, both known ex ante and independent from each other. We assume that firms are price takers and cannot adjust their price to demand shocks.[20] If we normalize price to 1, this means that sales fluctuate in any period between $\phi(1 + \varepsilon)$ in the high state $(t = h)$ and $\phi(1 - \varepsilon)$ in the low state $(t = l)$ at an exogenous rate ξ that measures the structural

[20] See Section 3.4 for the discussion of an extended model with an explicit formulation of entry and demand. While in our base setup presented here demand and productivity shocks may be homeomorphic, the extended model targets directly demand shocks that are the focus of our empirical work and eschews productivity shocks.

volatility of the economy. While we assume for simplicity that this rate is common to all firms, the timing of the shocks is a random event at the firm level, consistently with our empirical focus on the idiosyncratic component of firms' employment volatility.

Upon entry, firms choose a location or city defined by a (log) density $M > 0$. City choice determines firms' operating costs $R(M) \geq 0$ and job-filling rate $\mu(M) \geq 0$. $R(M)$ is a local index that combines all costs associated with maintaining an active position.[21] Importantly, firms that are not actively producing do not have to pay these costs. For example, if $R(M)$ represents the price of renting capital or real estate, this assumption means that there are no frictions on the capital market. Consistently with the patterns displayed in Section 2.3, we further assume that $R(M)$ and $\mu(M)$ are both increasing in M. The fact that $R'(M) > 0$ is easily justified by a congestion argument. Conversely, the sign of $\mu'(M)$ is more contentious because it depends directly on how many firms there are in each location, and what they do. For ease of exposition, we describe the framework in partial equilibrium, whereby those two local factors are not impacted by firms' decisions, and we defer the discussion on the endogenous determination of $\mu(M)$ to Section 3.4.

Strategies — Conditional on their location, firms also choose a strategy s, which in this context corresponds to a specific action to take in the low state. Firms can choose between three strategies $s \in \{B, W, C\}$. According to the "Business as usual" strategy (hereafter, denoted by B), if a firm is hit by a bad shock, it will keep paying its workforce or it will keep trying to hire. However, if operating costs are too high, the firm will seek to mitigate them by limiting the amount of time spent active in the low-production state. According to the "Wait-and-see" strategy (hereafter, denoted by W), if an active firm is hit by a bad shock, it will keep paying its workforce and wait for better times; yet, vacant firms, when hit by a bad shock, will postpone hiring until they have reached a high state again. Finally, according to the "Churning" strategy (hereafter, denoted by C), if a firm is hit by a bad shock, it will become idle. This means that it will wait if it is vacant and fire and wait if it is active.[22]

Recursive formulation — Given their choice of city and strategy (M, s), firms alternate between being vacant (V), active (A) or idle (I). They decide whether to operate or hire

[21] It may encompass wages, but those do not depend on firms' individual characteristics (ϕ, ε) in order to keep the focus on hiring decisions.

[22] As stated above, we reckon that, ultimately, these strategies endogenously affect $\mu(M)$. The effect of strategies on $\mu(M)$ is twofold: On the intensive margin (keeping the number of firms fixed), a higher share of firms following the B strategy should increase $\mu(M)$. Conversely, on the extensive margin, the opposite is true because, as argued below, more firms can enter if they are allowed to follow the W or C strategies.

while in a low state or not and this determines the firm's transition to a low state when posting a vacancy (with value $W_s(\phi, \varepsilon, M)$) or when filled (with value $C_s(\phi, \varepsilon, M)$). For any strategy s, firms' value functions are thus summarized as follows:

$$
\begin{aligned}
rV_s^h(\phi, \varepsilon, M) &= -c + \mu(M)[A_s^h(\phi, \varepsilon, M) - V_s^h(\phi, \varepsilon, M)] && (3)\\
&+ \xi[W_s(\phi, \varepsilon, M) - V_s^h(\phi, \varepsilon, M)] \\
rV_s^l(\phi, \varepsilon, M) &= -c + \mu(M)[A_s^l(\phi, \varepsilon, M) - V_s^l(\phi, \varepsilon, M)] && (4)\\
&+ \xi[V_s^h(\phi, \varepsilon, M) - V_s^l(\phi, \varepsilon, M)] \\
rA_s^h(\phi, \varepsilon, M) &= \phi(1+\varepsilon) - R(M) + \delta[V_s^h(\phi, \varepsilon, M) - A_s^h(\phi, \varepsilon, M)] && (5)\\
&+ \xi[C_s(\phi, \varepsilon, M) - A_s^h(\phi, \varepsilon, M)] \\
rA_s^l(\phi, \varepsilon, M) &= \phi(1-\varepsilon) - R(M) + \delta[W_s(\phi, \varepsilon, M) - A_s^l(\phi, \varepsilon, M)] && (6)\\
&+ \xi[A_s^h(\phi, \varepsilon, M) - A_s^l(\phi, \varepsilon, M)] \\
rI_s(\phi, \varepsilon, M) &= \xi[V_s^h(\phi, \varepsilon, M) - I_s(\phi, \varepsilon, M)] && (7)
\end{aligned}
$$

where r is the interest rate, c is the vacancy cost and δ is the exogenous component of the match destruction rate. Both c and δ are assumed to be fixed over time and constant across firms. Strategies determine the values of either posting a vacancy in the low state ($W_s(\phi, \varepsilon, M)$) or being active in the low state ($C_s(\phi, \varepsilon, M)$), as summarized in Table 4.

Table 4: Strategies and values of low state

	$W_s(\phi, \varepsilon, M)$	$C_s(p, \varepsilon, M)$
Business as usual	$V_B^l(\phi, \varepsilon, M)$	$A_B^l(\phi, \varepsilon, M)$
Wait-and-see	$I_W(\phi, \varepsilon, M)$	$A_W^l(\phi, \varepsilon, M)$
Churning	$I_C(\phi, \varepsilon, M)$	$I_C(\phi, \varepsilon, M)$

Entry, location choice and employment volatility — Since firms do not know in which state they will enter nor the state in any other period after entry, their expected profit at entry is given by $\mathbb{E}_s(\phi, \varepsilon, M) = 0.5 \times [V_s^h(\phi, \varepsilon, M) + W_s(\phi, \varepsilon, M)]$. Conditional on location, the *preferred strategy* s^* is thus the one that maximizes expected profit: $s^*(\phi, \varepsilon, M) = \underset{s}{\operatorname{argmax}}\, [\mathbb{E}_s(\phi, \varepsilon, M)]$.

For ease of exposition, we normalize the outside option to zero. Note that even preferred strategies may not be adopted if they yield a negative expected profit. In that case, the firm does not enter. Finally, under some conditions (detailed below), the model delivers a mapping $M^*(\phi, \varepsilon)$ between firms' characteristics and location:

$$M^*(\phi, \varepsilon) = \begin{cases} \underset{M}{\text{argmax}} \left[\mathbb{E}_{s^*(\phi,\varepsilon,M)}(\phi, \varepsilon, M)\right] \text{ if } \mathbb{E}_{s^*(\phi,\varepsilon,M^*(\phi,\varepsilon))}(\phi, \varepsilon, M^*(\phi, \varepsilon)) \geq 0 \\ \{\emptyset\} \text{ otherwise} \end{cases} \tag{8}$$

Productivity ϕ and volatility ε, together with strategy s and location M determine volatility of employment $\sigma(\phi, \varepsilon, M^*(\phi, \varepsilon), s^*(\phi, \varepsilon))$. The model predicts that under reasonable parametric conditions, churning may indeed be associated with higher employment volatility, as summarized in Proposition 1.[23]

PROPOSITION 1. ***Churning and employment volatility*** —Firms that adopt the churning strategy have a higher employment volatility if the structural volatility of the economy is low enough.

3.2 Solution

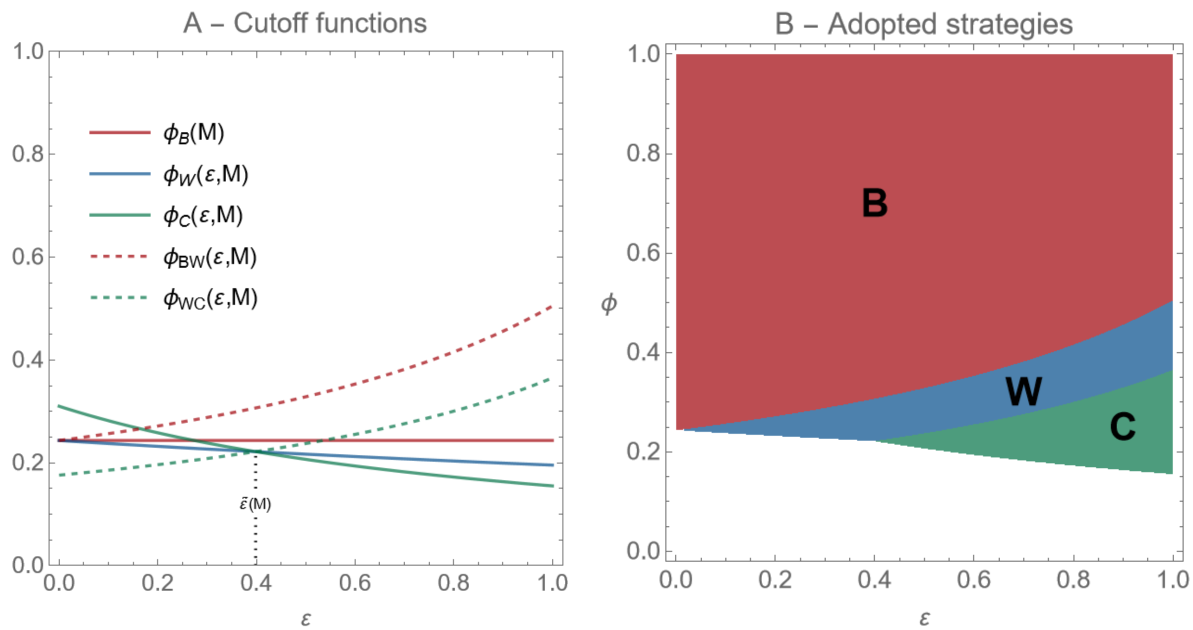
Firms jointly choose s and M. Yet, for exposition purposes, we solve the model in three steps. First, we detail how firms' characteristics determine their strategy choice, for a given location. Then, we compare strategy choices between different cities. Finally, we solve the general model.

Strategy choice — If we solve the system (3)-(7), we can make two observations: first, quite naturally, expected profit increases with productivity, regardless of the strategy; second, higher productivity is more profitable under strategy B than under strategy W, and under strategy W than under strategy C. Therefore, strategy choice is determined by five productivity cutoffs: three *selection cutoffs* $\{\phi_s(\varepsilon, M)\}_{s=B,W,C}$ that determine whether a given strategy is *feasible*, and two *switching cutoffs* $\phi_{BW}(\varepsilon, M)$ and $\phi_{WC}(\varepsilon, M)$ that compare strategies two-by-two and determine which strategy is preferred. If a strategy is both feasible and preferred, it is deemed *adopted*. These productivity cutoffs are represented in Panel A in Figure 4. While this figure is based on a somewhat arbitrary calibration, the qualitative insights represented hold true in general.[24]

[23] For high values of ξ, the model features the degenerate prediction that churning firms will mostly oscillate between the idle and the vacant states, with low associated volatility.

[24] The time unit is a year and we set $r = 3\%$. The match destruction rate δ is set to 10%, and the probability of switching between high and low demand states is set to 20%. The vacancy cost is set to 10% of a maximum productivity level $\overline{\phi}$, which is set to 1. We consider a cost function $R(M) = 0.2M^{0.1}$. This 10% elasticity stems from the addition of the 3% of urban costs calibrated by Combes et al. (2019) and 7% elasticity of raw wages (Ahlfeldt and Pietrostefani, 2019). Finally, we consider a worker finding rate given by $\mu(M) = 0.3M^{0.05}$. Note that one strategy may never be adopted, depending on the parameters. In

Figure 4: Strategy choice for a given city



Calibration: $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $\mu(M) = 0.3M^{0.05}$, $R(M) = 0.2M^{0.1}$, $c = 0.1$ and $\overline{\phi} = 1$. We set $M = 1$. Panel A: The figure represents the three minimum productivity cutoffs and the two strategy-switching cutoffs as a function of volatility ε. Panel B: The figure represents the set of (ε, ϕ) combinations associated with each adopted strategy. The blank section corresponds to combinations that are not feasible, regardless of the strategy.

Under strategy B, the selection cutoff $\phi_B(\varepsilon, M)$ does not depend on ε and may therefore be denoted $\phi_B(M)$. As is usual in this type of models, sales must cover both operating costs and the vacancy cost at entry and following any exogenous separation. Under strategy W, the selection cutoff $\phi_W(\varepsilon, M)$ is lower than under strategy B if $\varepsilon > 0$, and it decreases with ε. This strategy can therefore accommodate more volatile firms that have lower productivity in the low state compared to less volatile firms: by waiting, the firm mitigates the consequences of being in the low state. Finally, under strategy C, the selection cutoff $\phi_C(\varepsilon, M)$ is even more sensitive to ε than under strategy W: $\partial\phi_C(\varepsilon, M)/\partial\varepsilon < \partial\phi_W(\varepsilon, M)/\partial\varepsilon$. However, the selection cutoff also entails a fixed cost $c\xi/\mu(M)$, which corresponds to the additional time spent vacant. Therefore, only highly volatile firms may be able to churn. In particular, churning only allows for the entry of less productive firms if their volatility exceeds a given cutoff $\tilde{\varepsilon}(M)$, which depends on both local and common parameters.

We then turn to the conditions that determine when firms adopt a churning strategy over alternative strategies. The switching cutoffs verify $\phi_{BW}(\varepsilon, M) > \phi_{WC}(\varepsilon, M)$. These two

particular, W disappears when $c \to 0$. Conversely, C disappears for large enough values of c.

cutoffs, as well as the difference between them, are convex increasing functions of ε. Regarding the B strategy, we can note that $\forall \varepsilon, \phi_{BW}(\varepsilon, M) > \phi_B(M)$. Therefore, if strategy B is preferred, it is also feasible, and therefore, adopted. Conversely, strategies W or C may be preferred, yet unfeasible, if $\phi_{WC}(\varepsilon, M) < \phi_W(\varepsilon, M)$ or $\phi_{WC}(\varepsilon, M) < \phi_C(\varepsilon, M)$. Equipped with these definitions, we can fully characterize the distribution of adopted strategies as a function of ϕ and ε. They are represented in Panel B in Figure 4 in the form of the three regions labeled B, W, and C. Panel B highlights our first two key results that hold for a fixed value of M, as summarized in Proposition 2:

Proposition 2. ***Strategy choice*** — In a given city,

2.1 Churning is adopted by more volatile, less productive firms.

2.2 Very volatile firms may churn even if they are quite productive. Conversely, low-productivity firms may be able to operate if they are volatile enough.

The joint strategy/location problem — The next step is understanding how density interacts with firms' productivity, volatility, and strategy choice. To proceed, we make three further assumptions:

Assumption 1. Churning happens in equilibrium.

Assumption 2. For each strategy, selection on productivity does not decrease with density.

Assumption 3. For each strategy, there exists an optimal level of density.

Those assumptions restrict the analysis to cases where the model is both relevant (Assumption 1), realistic (Assumption 2), and analytically well-defined (Assumption 3).[25] Under those assumptions, we can perform comparative statics of strategy choice under different city sizes, which yields the following results, summarized in Proposition 3:

[25] Assumption 1 is verified under the condition $\tilde{\varepsilon}(M) < 1$, which is equivalent to $c/\mu(M) < R(M)/\xi$. In words, this means that the expected vacancy cost is lower than the operating costs paid by the firm when it is operating in the low state. For simplicity, we will even assume a stronger condition, stating that $\forall M \geq 0, R(M) > c$ and $\mu(M) > \xi$. Note that this assumption means that both $R(M)$ and $\mu(M)$ feature a fixed positive component, or that there is a lower bound for density, as we do in our calibration. Regarding Assumption 2, the most binding condition is for strategy C, where it is equivalent to: $\forall M \geq 0, R'(M) \geq (r + \delta + \xi)\mu'(M)/\mu(M)^2$. For simplicity, and using Assumption 1, we will even assume a stronger condition on the ratio of the elasticity of each function: $\forall M \geq 0, \epsilon_{R,M}/\epsilon_{\mu,M} > (r + \delta + \xi)/\xi$. Assumption 3 means that $\forall s, \exists M > 0$ s.t. $\partial \mathbb{E}_s(\phi, \varepsilon, M)/\partial M = 0$. As for Assumption 2, this assumption will be met if the ratio of the cost elasticity to the matching elasticity is high enough.

Proposition 3. ***Comparative statics*** — If cities are heterogeneous in density,

3.1 Denser cities have a higher share of churning firms.

3.2 Low-productivity firms are more volatile in denser cities.

Results 3.1 and 3.2 can also be gauged by comparing adopted strategies in the (ε, ϕ) plane for different levels of density, as we do in Panel A of Appendix Figure C.1. In line with result 2.2, even productive firms may churn in denser cities if they are very volatile. In addition, higher volatility is more conducive to the entry of low-productivity firms, as shown by a steeper lower bound of the colored area.

Finally, we study the firm location choice, and how churning interacts with the spatial sorting of firms based on their productivity. This requires solving a global maximization problem, to identify the density chosen by firms, conditional on their productivity ϕ and volatility ε. While the combinations of (ϕ, ε) associated with strategy choice are only defined implicitly, the envelope theorem ensures that Proposition 2 is robust to firms' location choice. Panel B in Appendix Figure C.1 illustrates this result. In particular, more volatile firms are more likely to adopt the churning strategy, more productive firms are more likely to adopt the business-as-usual strategy, and low-productivity, high-volatility firms are more likely to be able to operate if they adopt the churning strategy.

3.3 Volatility and the sorting of firms

This framework allows us to study how the joint strategy/location optimization problem at the individual firm level translates into aggregate sorting patterns of firms across space. Conditional on selection and strategy choice, the spatial sorting of firms is implicitly defined by the optimal productivity/volatility-density relationship described by *sorting cutoffs* $\phi_s^*(\varepsilon, M) = \underset{\phi}{\operatorname{argmax}}\, [\mathbb{E}_s(\phi, \varepsilon, M)]$ and $\varepsilon_s^*(\phi, M) = \underset{\varepsilon}{\operatorname{argmax}}\, [\mathbb{E}_s(\phi, \varepsilon, M)]$.

These sorting cutoffs illustrate how matching economies work in this model. Since high-productivity and high-volatility firms have more to gain from being able to hire more quickly, there is positive sorting with respect to productivity and volatility, for a given strategy. In addition, given the multiplicative structure between ϕ and ε, high-productivity (resp., high-volatility) firms have all the more to gain from locating in denser cities if they are more volatile (resp., productive). Formally, we have $\forall \varepsilon \in [0,1], \partial\phi_B^*(\varepsilon, M)/\partial M \geq \partial\phi_W^*(\varepsilon, M)/\partial M \geq \partial\phi_C^*(\varepsilon, M)/\partial M$. Therefore, even if more productive firms sort into denser cities, the share of churning firms also increases with density and the productivity-density gradient decreases with firm volatility.

These patterns are summarized in Proposition 4:

PROPOSITION 4. ***Predictions*** — If firms choose their location in order to maximize their expected profit upon entry,

4.1 More productive and more volatile firms sort into denser cities.

4.2 Productivity and volatility are complementary in city choice.

4.3 The share of churning firms increases with density and the productivity-density gradient is flatter for more volatile firms.

Prediction 4.3 echoes the aggregate sorting patterns described in Section 2. Appendix Figures C.2 and C.3 illustrate this prediction for the same calibration of the model, for a density spanning between 1 and 10. Figure C.2, consistent with Panel B of Figure 1, displays the share of churning firms as an increasing function of density. In Figure C.3, consistent with Figure 2 , we plot the predicted average productivity for each decile of M and ε and show a decreasing productivity-density gradient with firm volatility. As for predictions 4.1 and 4.2, they will be tested in Section 4.

3.4 Discussions

In order to maintain analytical tractability, the model rests on several simplifying assumptions. We briefly discuss here the robustness of its conclusion to a more general framework.

Endogenous matching rate — In the presentation, it was assumed that the worker meeting rate was not affected by firms' location decisions and strategies. However, such assumption is not internally consistent, because the worker meeting rate depends on the local market tightness, which is, itself, an equilibrium outcome. A priori, the impact of churning on market tightness is ambiguous. On the intensive margin, churning firms lay off workers while remaining idle, which loosens the market; conversely, churning may also allow more firms to enter. To recover market tightness, we need to define a fixed point problem that describes steady-state conditions and to specify a process for firm entry, in order to determine the equilibrium firm-to-worker ratio. In Appendix C.4, we describe a way of tackling this extended model. Using simulations, we show that, under plausible parametric assumptions on the matching technology, the resulting worker meeting rate is an increasing concave function of density, even if the positive effect of churning on firm entry mitigates the magnitude of agglomeration economies.

We also use this framework to explain why in general equilibrium, the assumption that demand shocks are uncorrelated across firms is an important driver of agglomeration economies based on firm volatility. If the main source of volatility at firm level was business cycle shocks, volatile firms would all end up trying to hire at the same time, thereby creating a negative externality of labor market crowding. However, as argued in Section 2, most fluctuations observed in firm-level data are driven by idiosyncratic shocks. In addition, previous studies have shown that net entries do not contribute much to aggregate volatility, thus suggesting that the cyclical component of net entries is not strong (di Giovanni et al., 2014).[26] As a consequence, we expect the benefit of the agglomeration of volatile firms in dense cities to dominate the consequences of firms' hiring needs crowding out during business cycle booms. The evidence provided in Section 4 is consistent with this view.

Match quality – While the baseline model assumes that the benefits of density only come from faster hiring, there are other known sources of agglomeration economies. In particular, as discussed in Section 2.3, the matching process may be more efficient in large cities in the sense that the resulting firm-worker matches are more likely to be more productive. In Appendix C.5, we describe an extended model where match quality is stochastic and good matches are more likely in larger cities. If good matches are unlikely, firms may adopt a partial churning strategy whereby they only churn workers in bad matches. This strategy may dominate the business-as-usual strategy for a wide range of parameters, and result in a higher churning rate overall. Conversely, if good matches are likely, firms may also have the incentive to churn because it is not risky in terms of future match prospects. These two opposite forces make it impossible, without further structure, to predict whether neglecting match quality results in an upward or downward bias in the correlation between employment volatility and city size.

Firm size heterogeneity and demand — In the presentation, we did not model demand nor allowed for firm size heterogeneity linked with productivity. In Appendix C.6, we embed this model in a framework à-la Melitz (2003), where monopolistically competitive firms face a CES demand system and draw heterogeneous productivity and demand volatility upon entry. This extended model allows us to better understand the underlying differences in the behavior of firms that face demand shocks and either adopt the Business-as-usual or the Churning strategy. Under the former, firms adjust their prices, while under the latter, prices

[26] We have also checked that the entry decisions used in Section 4 do not show strong cyclical patterns.

are independent from individual demand shocks, which are then passed on employment. We show that under plausible parametric restrictions, the main predictions of the base model carry through: churning makes it possible for lower productivity firms to enter, the share of volatile firms increases with density, and the productivity-density gradient is flatter for volatile firms.

4 Volatility and firm location: empirical evidence

In this section, we turn back to our data and describe two tests of the main predictions of the model. These tests rely on different assumptions and proxies for firm characteristics introduced in Section 3.

4.1 Demand shocks

As argued in Section 3, employment volatility varies with the firm's strategy choice, which depends on the joint impact of the firm's productivity and *structural* volatility, both directly and indirectly through its impact on location decisions. Conditional on these structural characteristics, a dense location may actually cause an increase in employment volatility. A direct consequence is that the measure of employment volatility used in Section 2.2 is endogenous to the firm's management practices. In this section, we thus introduce two alternative measures of volatility that exploit exogenous variations in demand at firm-level.

Product demand — The first measure uses exogenous variations in demand for products in the firm's portfolio adapted from Hummels et al. (2014). Therefore, we focus on demand shocks (and their volatility) that a firm can expect to face, conditional on the nature of its production. We build time-series of expected demand growth at firm-level using the structure of the firm's product portfolio, and the growth of product-level demand, measured from trade data. Details are available in Section A.4 in the Appendix. The structure of a firm's product portfolio is measured using the EAP survey, which covers all manufacturing firms beyond 20 employees. For each firm, we know the product-level breakdown of their sales, which we can use to measure exposure to product-level demand shocks. The monthly growth of product-level demand is calculated using import data for all European countries, but France. The implicit assumption is that the demand emanating from foreign markets is sufficiently correlated with the overall demand addressed to French firms so that the growth of imports is a reasonable proxy for demand shocks. The firm-level series of demand shocks are constructed as an average of product-level import growth, weighted by the share of each product in the firm's portfolio.

Sectoral demand — The second measure uses exogenous variations in the expected demand addressed to French firms, conditional on their sector. It is constructed using detailed input-output tables and monthly sectoral growth rates of sales at the national level. Given information on the firm's main sector of activity, we use IO tables to measure the firm's exposure to different downstream sectors, through input purchases. We then construct a measure of demand growth, that we define as an IO-weighted average of the growth of sales of firms located in downstream sectors. While for most firms this measure captures sectoral demand variations, multi-establishment firms may be exposed to different downstream shocks, which we take into account while aggregating across establishments of the same firm within a CZ. Firms with multiple establishments in different sectors within the same CZ constitute less than 0.9% of the sample, however. Details on the construction of this variable are available in Section A.5 in the Appendix. In terms of sectors, we focus on manufacturing and most service sectors (dropping agriculture, the public sector, finance and insurance, production and distribution of energy &water, sanitation and waste management, and other services). We also drop non-tradable sectors such as accommodation and food services (sectors 55 and 56 in the Nomenclature d'activités française – NAF rév. 2) and real estate (sector 68).

Note that, by definition, these alternative measures of demand shocks cover very different samples: While the use of product demand forces us to focus on large manufacturing firms, the alternative measure recovered from input-output data allows for a broader coverage, including firms in manufacturing but also business services, logistics or commerce.

4.2 Demand shocks and changes in employment

The variables described in Section 4.1 are meant to capture demand-driven sources of employment volatility. The underlying assumption is that firms exposed to demand shocks, through specific products in their portfolio or specific firms in downstream sectors, respond by adjusting labor demand. We now provide evidence of such endogenous adjustments using local projection methods.[27]

Empirical strategy — We use the monthly panel of firms active in the January 2015 cross-section, over 2012-2017. The estimated baseline equation takes the following form:

$$\ell_{f,t+h} - \ell_{f,t-1} = \beta^h \gamma^D_{f,t} + \gamma X_{ft} + \varepsilon_{f,t} \tag{9}$$

[27]See Jordà (2023) for a review of the literature, with applications to panel data.

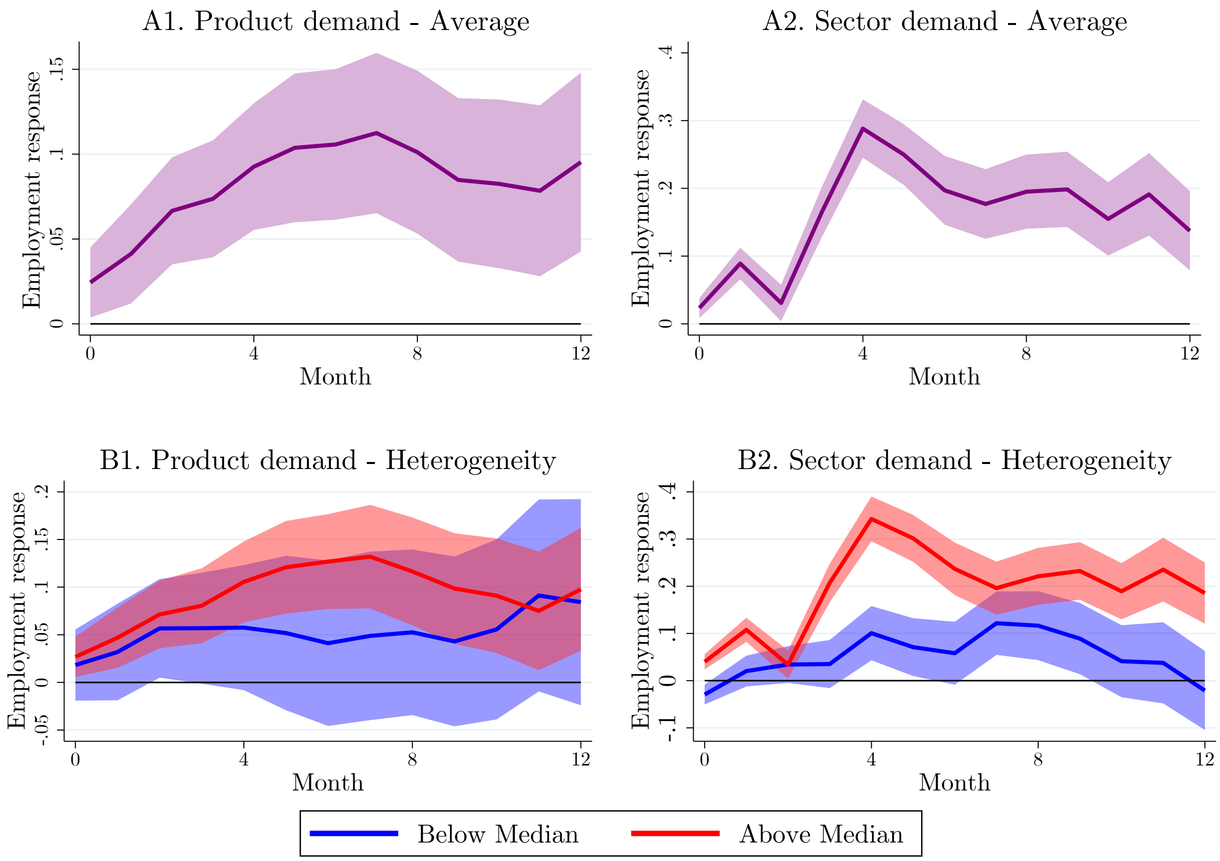
where $\ell_{f,t}$ denotes the log of employment of firm f at time t, and $\gamma^D_{f,t}$ the demand shock that affects firm f between periods $t-1$ and t (at the monthly level). Equation (9) estimates the impact of a demand shock $\gamma^D_{f,t}$ on the cumulative growth of employment over the h months that follow the shock. The matrix X_{ft} of controls contains period fixed effects, which absorb the effect of all commonalities affecting firms, leads, and lags of the demand variable, to account for the serial correlation of shocks, as well as lags of the growth rate of employment, which helps to take care of remaining endogeneity issues.[28]

Results — Figure 5 reproduces the impulse response functions recovered from the estimation of equation (9) over a 12-month horizon. The left panels use the measure of demand shocks recovered from the product-level growth of foreign demand, and the right panels use those estimated from downstream sectors' sales growth. Note that the estimation sample is substantially larger with the latter, as the demand shock recovered from product-level data is restricted to relatively large firms in the manufacturing sector. This explains wider confidence intervals in the former case. Panels A1 and A2 show that in both cases, the employment effect of demand shocks is already significant within two months. It takes around four months for the effect to stabilize, which is consistent with the existence of hiring frictions. Although the shape of the impulse response functions is roughly similar, the magnitude is larger when demand shocks are estimated using sectoral sales data in downstream sectors. A possible explanation is that shocks to foreign demand, which are used to construct the product-based variable, are less correlated with overall firm sales. This would be the case if foreign sales represent a limited share of a firm's total sales, and demand is not perfectly correlated across countries as is typically the case in the data (Caselli et al., 2020, di Giovanni et al., 2014).

Panels B1 and B2 provide suggestive evidence that the pattern of these adjustments systematically varies over space. More specifically, we re-estimate impulse response functions, allowing for the adjustment to vary between more and less dense commuting zones. Results suggest that labor demand adjustments are larger and faster in the short run in commuting zones with above-the-median densities. When product-level data are used to measure demand shocks, the average response of labor demand is not significant in less dense cities while the estimated effect of demand shocks is already significant on impact, and remains so

[28]When we use the measure of demand shocks recovered from product-level export data, we can further control for sector×period fixed effects, and identify the labor demand responses to shocks from the heterogeneity across firms from the same sector. Results, available upon request, are robust. The alternative measure of demand constructed from downstream sectors' sales growth exploits the sector dimension which implies that we cannot include fixed effects at the sector×period level.

Figure 5: Impulse response functions of employment to demand shocks



Notes: The figure reproduces impulse response functions recovered from the estimation of equation (9) over a 12-month horizon ($h = 0/12$) and correspond to the employment response (in %) following a demand shock. Panels A1 and B1 use the "product demand" variable constructed from product-level foreign demand growth rates and Panels A2 and B2 use the "sector demand" variables that averages sectoral growth rates based on input-output coefficients. Panels A1 and A2 show the average effect, while in panels B1 and B2 the effect is allowed to vary according to whether the firm is located in a CZ below or above median density. The estimated coefficients (β^h) are normalized by the standard deviation of the corresponding demand shock. The shaded areas correspond to confidence intervals at 90%.

during the next year, in above-the-median-density cities. When sector-level data are used to measure demand shocks, the difference between above- and below-the-median-density cities is even starker.

Together, these results thus confirm a causal employment response to estimated demand shocks. Based on this insights, we then build two measures of demand-driven volatility, which we construct as the standard deviation of demand shocks:

$$\varepsilon_{f,t} = \sqrt{\frac{1}{2\omega+1}\sum_{\tau=-\omega}^{\omega}(\gamma_{f,t}^{D} - \bar{\gamma}_{f,t}^{D})^2}$$

See details in Appendix A.4 and A.5. Tables A.2 and A.3 in the Appendix describe the robust positive correlation between these measures of demand-driven volatility and idiosyncratic employment volatility in the January 2015 cross-section that we studied in Section 2.2. Despite somewhat different samples, the correlation between volatility and firm's age or productivity is very similar to that described in Table 3.

4.3 Location choice

Empirical strategy — Armed with two alternative measures of demand-driven volatility, we can now test the model's predictions regarding the spatial sorting of firms displaying heterogeneous productivity and volatility. Our empirical framework is based on a location choice model estimated with a conditional logit estimator (CLM). Since our theoretical model focuses on firm entry decisions, not firm survival, our samples reflect the event of firm creation.

We construct two samples of firm creation events between 2010 and 2019, using the two distinct measures of demand volatility described in Section 4.1. The first sample is based on firm creation events for which we have information on the firm's portfolio of products at entry, i.e. no later than two years after its creation, as the firm's decision to expand its product scope may also be endogenous.[29] For consistency, we also compute productivity over this two-year period.[30] We end up with a sample of 1,682 firm creations (see Table B.6 in the Appendix for details). The second sample is based on all firm creation events between 2010 and 2019 for firms that match the selection criteria detailed in Section 4.1. We use the structure of the firm in the first year of its existence to weight sector demand shocks across its different plants.[31] As in the first location choice model sample, we compute productivity

[29] In addition, world demand used to construct synthetic demand growth is based on the 12 months before and including the firm's creation month. Details are available in Section A.4 in the Appendix.

[30] Note that this strategy rests on the assumption that there is no causal effect of a firm's location on its TFP. Using the same data for the year 2000, Gaubert (2018) estimates that half of the productivity advantage of large cities comes from the sorting of firms on their exogenous productivity.

[31] This is measured by the distribution of employment in full-time equivalent terms across the firm's different plants. In addition, expected sectoral demand volatility is calculated as the standard deviation of monthly sectoral demand shocks over the 12 months before and including the firm's creation month. Details are available in Section A.5 in the Appendix.

over the first two years after the firm's creation. The final sample includes 56,096 firm creations (see Table B.7 in the Appendix for details).

While the theoretical model assumed a continuum of densities, we now consider a discrete set of locations $\mathcal{M} = \{M\}$. Conditional on the firm's decision to enter the French market, we model the choice of a location as a function of the firm's and the location's attributes. We borrow the notations from Section 3 and denote $\mathbb{E}^*(\phi_f, \varepsilon_f, M) = \mathbb{E}_{s^*(\phi_f,\varepsilon_f,M)}(\phi_f, \varepsilon_f, M)$ for brevity. Assuming that the expected inter-temporal profit in each location can be decomposed into a deterministic and a random component e_{fM}, one can write the probability of a firm f choosing a location M as:

$$
\begin{aligned}
\mathbb{P}\left(f \text{ chooses } M | e_{fM}\right) &= \mathbb{P}\left(\mathbb{E}^*(\phi_f, \varepsilon_f, M) + e_{fM} > \max_{M' \neq M} \left\{\mathbb{E}^*(\phi_f, \varepsilon_f, M') + e_{fM'}\right\}\right) \\
&= \frac{\exp\left[\mathbb{E}^*(\phi_f, \varepsilon_f, M)\right]}{\sum\limits_{M' \in \mathcal{M}} \exp\left[\mathbb{E}^*(\phi_f, \varepsilon_f, M')\right]}
\end{aligned}
$$

where the second line uses the assumption that e_{fM} are i.i.d. draws from a type-1 extreme value distribution.

Our model predicts the choice between all commuting zones to be a function of the size of operating costs $R(M)$ and the job-filling rate $\mu(M)$ as well as their interaction with firms' productivity ϕ_f and volatility ε_f. Following the theoretical model, the CLM considers the role of commuting zone density and its interaction with firms' characteristics, productivity and volatility.

Control variables — To isolate the effect of density, we also control for other commuting zone characteristics that are important for firm location decisions, namely two measures of workforce skill (the share of managers and the share of college graduates),[32] and two measures of labor market tension (the unemployment rate and the activity rate among the working age population).[33] In order to verify that other local characteristics correlated with density do not drive our results, we test the robustness of our estimates to the inclusion of CZ fixed effects.

The identification assumption behind the CLM is that other firm characteristics that are

[32]The share of managers is calculated from DADS-INSEE, where managers are defined by 1-digit occupation (CS1) equal to 2 or 3. The share of college graduates is obtained from Census data. Both of these variables are measured in the year of the firm's creation and expressed as logs.

[33]Data is obtained from the INSEE. The working age population includes individuals aged 15 to 64. Both of these variables are measured in the year of the firm's creation and expressed as logs.

correlated with volatility and productivity do not interact with density in determining location choice. However, this assumption is unlikely to be true in general. In particular, there is ample evidence that firms benefit from having other firms in the same industry operating in the same area (Combes and Gobillon, 2015). To this end, we construct Balassa indices of revealed comparative advantage of each CZ as a location destination. We consider two measures of comparative advantages: (i) a proxy for access to downstream demand in a CZ; (ii) a proxy for access to upstream suppliers in a CZ. Section A.6 in the Appendix provides further details. We control for these indicators of localization economies measured in the year preceding the year of the firm's creation.

Results: Sorting on volatility and productivity — Estimation results are summarized in Table 5 using the product demand volatility in Panel A and the volatility of downstream sectors in Panel B. In column (1), we show the coefficient associated with the (log of) density of the commuting zone, and we confirm the tendency of firms to agglomerate in denser commuting zones, even after controlling for other commuting zone characteristics, including measures of localization economies.[34] In columns (2) and (3), we then interact density with the model's relevant firms characteristics, namely productivity and volatility. Column (2) confirms previous results in the literature, showing that more productive firms are more likely to locate in denser cities. In column (3), we find that volatile firms are also more likely to locate in dense cities. In column (4), we simultaneously consider the two interaction terms in order to tackle the possible correlation between productivity and demand volatility. Finally, column (5) further controls for CZ fixed effects and solely identifies the coefficients on the interaction terms.

Results point to a positive and non-negligible impact of both productivity and demand volatility on location patterns, which is stable across specifications. Column (4) shows that the elasticity of the odds of choosing a location to the density of this commuting zone increases from .26 to .40 when moving from the first to the ninth decile of the distribution of productivity. As for demand volatility, the effect is slightly lower than for productivity (and possibly larger for sectoral demand volatility in Panel B than for product demand volatility in Panel A), but it is not negligible. Our estimates from Column (4) suggest that the elasticity of the odds of choosing a specific location to the density of this commuting zone increases from .30 to .34 (resp., 0.48 to 0.54) when moving from the first to the ninth

[34] Detailed estimation results are available upon request. Both measures of revealed comparative advantage at the sector level have a large positive effect on firms' location choice.

Table 5: Results of the location choice model

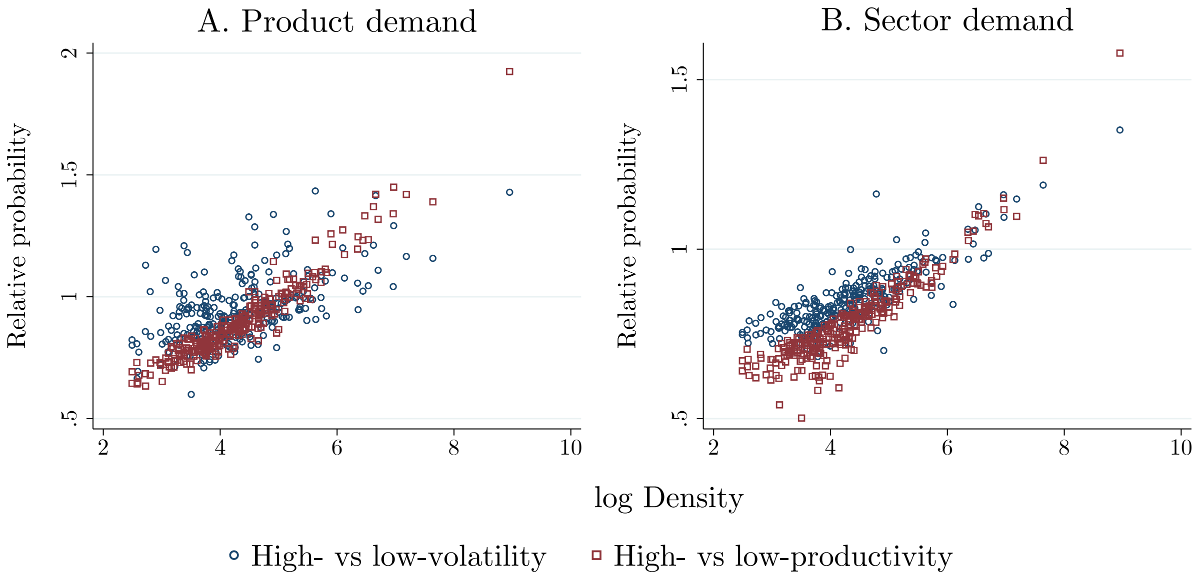
	Dependent Variable: CZ choice						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Product demand volatility						
CZ Density M	0.323	0.319	0.322	0.319		0.319	
	(0.033)	(0.033)	(0.033)	(0.033)		(0.033)	
- × Productivity		0.070		0.069	0.062	0.054	0.048
		(0.017)		(0.017)	(0.015)	(0.031)	(0.029)
- × Volatility			0.033	0.030	0.027	0.015	0.013
			(0.018)	(0.018)	(0.016)	(0.031)	(0.029)
- × Volatility × Productivity						0.024	0.021
						(0.040)	(0.037)
Pseudo R2	0.057	0.058	0.057	0.058	0.099	0.058	0.099
N. observations	471K	471K	471K	471K	471K	471K	471K
	Panel B: Sector demand volatility						
CZ Density M	0.512	0.511	0.512	0.510		0.510	
	(0.005)	(0.005)	(0.005)	(0.005)		(0.005)	
- × Productivity		0.059		0.059	0.050	0.051	0.043
		(0.003)		(0.003)	(0.002)	(0.004)	(0.004)
- × Volatility			0.023	0.022	0.012	0.015	0.006
			(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
- × Volatility × Productivity						0.012	0.011
						(0.005)	(0.005)
Pseudo R2	0.182	0.183	0.183	0.183	0.205	0.183	0.205
N. observations	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M
CZ characteristics	✓	✓	✓	✓		✓	
Intermediate demand and supply	✓	✓	✓	✓	✓	✓	✓
CZ fixed effects					✓		✓

Notes: Coefficient estimates from a conditional logit model with firm fixed effects. Panel A: The sample is based on all firm entries from January 2010 to December 2019 (1,682 entries, resulting in $N = 470,960$ observations) with documented product demand volatility. Panel B: The sample is based on all firm entries from January 2010 to December 2019 (56,096 entries, resulting in $N = 15,706,880$ observations) with documented Input-Output demand volatility. M is the log of CZ density. Both volatility, productivity, and the product of the two are standardized by year of creation. Standard errors in round parentheses.

decile of the distribution of product demand volatility (resp., sectoral demand volatility). These results are consistent with Prediction 4.1 in the model.

The heterogeneity in the determinants of location choices along the distribution of firms is further illustrated in Figure 6, which compares the predicted probabilities of locating in a particular commuting zone, for firms at the 75th percentile relative to the 25th percentile of

Figure 6: Heterogeneity in location choices, along the distributions of productivity and demand volatility



Notes: The figure shows the mean probability of locating in each commuting zone, for high-productivity (respectively, high-volatility) firms in relative terms with low-productivity (respectively low-volatility) firms. The cutoffs are based on firms at the 25th and 75th percentile of each distribution. In Panel A, volatility is defined by the standardized volatility of product demand and the probabilities are recovered from the estimation of the model in column (4) of Panel A of Table 5. In Panel B, volatility is defined by the standardized volatility of sectoral demand and the probabilities are recovered from the estimation of the model in column (4) of Panel B of Table 5.

the distribution of firms' productivity and demand volatility. The patterns recovered from heterogeneous productivity and volatility are quite similar, even if there is more noise on product demand volatility (Panel A), possibly because of the smaller sample size. In both cases, the conditional location probabilities are roughly equal at a density of around 150, which corresponds to the level observed in commuting zones in the top 25th percentile of the population density distribution. Above this level, both high productivity and high volatility firms are more likely to locate in denser cities. However, this figure also suggests that sorting remains higher along the productivity dimension, especially for the highest levels of density.

Results: Combined effects — Finally, we turn to Prediction 4.2, whereby productivity and volatility are complementary in firms' location choices. In other words, more productive (respectively, volatile) firms are all the more likely to sort into denser locations when they are more volatile (respectively, productive). This prediction stems from the multiplicative structure between ϕ and ε in the model. Therefore, by looking at the impact of the interaction between firm productivity and firm volatility on firms' location choice, we can gauge the importance of complementarity between those two dimensions.

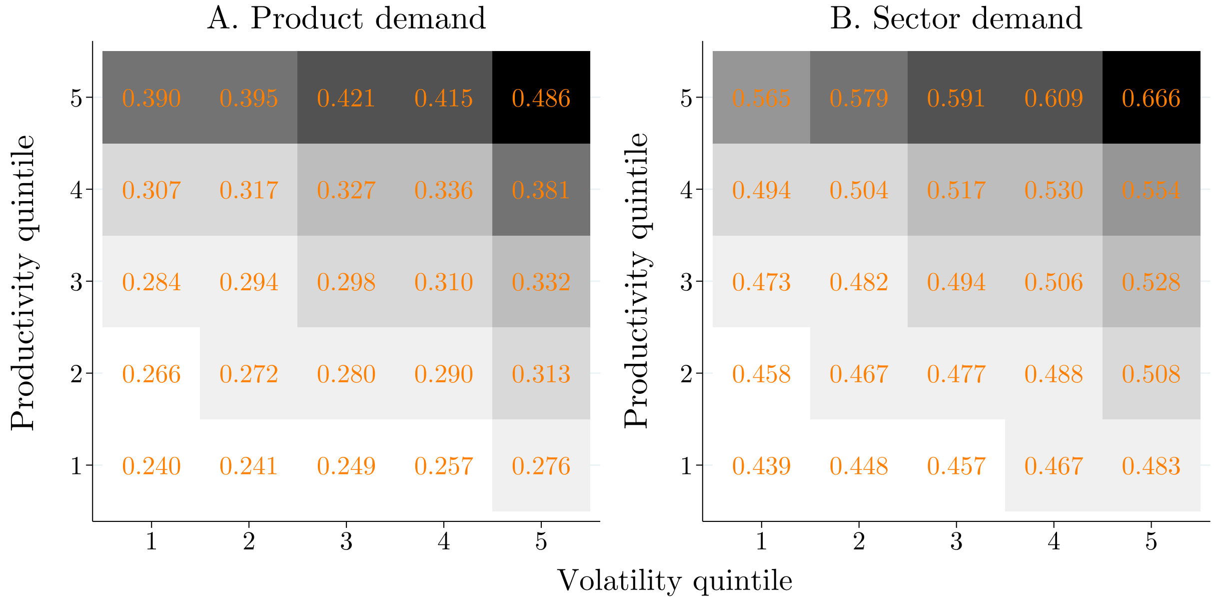
In Column (6) of Table 5, we estimate the impact of the triple interaction between CZ density, firm productivity, and firm demand volatility. The coefficient on the triple interaction is positive and remains so when we further control for CZ fixed effects (column 7). The coefficient is not statistically significant in the small sample in Panel A, but is significant at the 1% level when we estimate the augmented model in the larger sample (Panel B). This suggests that Prediction 4.2 is verified in the data.

In order to get a sense of the magnitude of this complementarity, we compute the elasticity of the odds of locating in a given CZ to CZ density, for different quantiles of productivity and volatility. Results are displayed in Figure 7. Panel A shows that when going from the first to the last quintile of productivity, the elasticity increases by 63% for firms at the first quintile of product demand volatility and by 76% for firms at the last quintile of product demand volatility. The complementarity between productivity and volatility computed from sectoral demand is also quantitatively meaningful, even if the base values are different: when going from the first to the last quintile of productivity, the elasticity increases by 29% for firms at the first quintile of sector demand volatility and by 38% for firms at the last quintile of sector demand volatility (Panel B).

This difference between low and high-volatility firms is largely due to the fact that in both samples, low-productivity firms hardly sort by demand volatility, while low-volatility firms still sort by productivity. The structure of our model allows for this possibility: When productivity is close to zero, so is expected profit, regardless of location. Accordingly, whether or not such an asymmetry is observed or not in the data depends on the intensity of firm selection by productivity, which our results suggest is sizable in both samples.

Robustness and Mechanisms — In Table B.9 in the Appendix, we replicate columns (4) and (6) of Table 5 with different specifications to assess the robustness of our results and interpretations. First, columns (3) and (4) show that failing to control for other CZ characteristics correlated with density results in much higher coefficient estimates on log density, but does not affect the estimates of the interaction terms. This suggests that the sorting on density along the productivity and volatility dimensions is not driven by other local characteristics. Second, we show in columns (5) and (6) that failing to control for localization economies at the sector level results in slightly higher coefficient estimates for our variables of interest, but of the same order of magnitude. Third, we show in columns (7) and (8) that the coefficients are fairly stable if we do not control for firm fixed effects, thus

Figure 7: Elasticity of the odds of choosing a CZ to CZ density



Notes: Each cell is computed in two steps. First, for each firm of productivity ϕ and volatility ε in the estimation sample, we compute the predicted elasticity (in %) as $\exp\{0.01[\hat{\beta}_M + \hat{\beta}_{M\phi}\text{std}(\phi) + \hat{\beta}_{M\varepsilon}\text{std}(\varepsilon) + \hat{\beta}_{M\varepsilon\phi}\text{std}(\varepsilon\phi)]\} - 1$, with $\text{std}(x)$ the standardized value of variable x and β_M, $\beta_{M\phi}$, $\beta_{M\varepsilon}$, and $\beta_{M\varepsilon\phi}$ the coefficient estimates displayed in column (6) of Table 5, for the corresponding panels. This value is then averaged over all firms that belong to a given combination of productivity-volatility quintile.

suggesting that they are not driven by spurious correlation stemming from a too saturated model. Finally, we allow firms to sort differentially on density based on their sector. Note that this extension is only feasible with our second definition of volatility, which is defined over multiple sectors. To that end, we further control for the interaction of a binary variable indicating the firm's sector (in six categories) and log CZ density, using the manufacturing sector as the baseline. Even if all the coefficients on these interaction variables are large and positive because firms that belong to the manufacturing sectors tend to locate in less dense areas, columns (9) and (10) show that including those interactions does not affect the estimated values of our variables of interest.

In order to delve into the mechanisms behind these observed sorting patterns, we finally make use of firms' heterogeneity regarding the skill intensity of their labor demand. Firms that rely more on low-skilled workers should be less likely to locate in denser areas, because of worker sorting along the skill dimension. In addition, provided there is complementarity between firm and worker productivity, high-productivity firms should be less likely to locate in denser areas when they rely on a high share of low-skilled workers. Conversely, since low-skilled workers are more easily replaceable, firms that rely on a high share of low-skilled workers should be more likely to act on their structural volatility by locating in denser areas. Table B.10 in the Appendix shows that these three predictions are borne in the data, at least in the sample where volatility is computed from sector demand: in particular, sorting on volatility is driven by the firms with a relatively high low-skilled labor demand.

5 Conclusion

This paper shows that firms with a more volatile activity benefit from locating in denser locations. Higher operating costs associated with density create an incentive for volatile firms to adopt a more flexible workforce management strategy. In turn, by frequently releasing workers, those firms generate a positive externality on other firms, which benefit from easier hiring conditions. This finding opens a fruitful avenue for future research on the determinants of the spatial distribution of economic activity that go beyond static characteristics such as productivity. It provides a novel explanation for the non-negative correlation between city size and unemployment rates, and for the observation that many low-productivity firms are able to operate in large cities.

A natural question that arises is whether such sorting patterns are optimal: is it desirable for more volatile firms to concentrate in bigger cities despite lower productivity? Should cities be encouraged to diversify their local economic fabric towards a large number of small firms that offer higher re-employment insurance, at the expense of large local champions? However, answering these important questions would require a more structural modelling of the labor (and possibly real estate) market. So far, our partial-equilibrium analysis has overlooked many effects. For example, workers should be compensated for working in more volatile firms. Conversely, a higher proportion of volatile firms could reduce urban congestion costs if firms can adjust their operating expenses. Large firms may also want to consider the potential trade-offs between monopsony power in small labor markets and the flexibility offered by large ones. We will leave these extensions for further research.

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A Data Appendix

A.1 Sample selection

Table A.1: Sample selection

	Operating in January 2015	Relevant sectors	Single CZ	2 or more employees	Non-missing productivity
Number of firms	890,088	770,901	609,662	457,486	316,041
Number of plants	1,100,329	934,894	672,556	512,949	356,888
Total employment	11,954,963	10,385,953	5,474,535	5,320,256	3,641,250

Notes: Number of firms refers to the concept of firm described in the main text, i.e. we aggregate plants of the same firm within each commuting zone. In column (1), we count firms operating in January 2015 with non-missing employment volatility. Column (2) keeps only the relevant sectors for our analysis: manufacturing, construction and service sectors (including non-tradable services). Column (3) drops firms operating in more than one CZ. In column (4) we keep firms with at least two employees, measured in full-time equivalent terms. In column (5), we keep only firms with non-missing productivity and age (i.e. firms for which we do not have information on the date of creation).

A.2 Skill groups

Skill groups are defined following Combes et al. (2012). The low-skill group includes low-skill blue collars (in craft and manufacturing) and low-skill white collars (sales clerk, employees in personal services). The corresponding occupational codes in the French classification are: 55, "employés de commerce"; 56, "personnels des services directs aux particuliers"; 67, "ouvriers non qualifiés de type industriel"; 68, "ouvriers non qualifiés de type artisanal". The intermediate-skill group includes high-skill blue collars (in craft, manufacturing, handling, and transport), and intermediate-skill white collars (administrative employees). In the French standard occupational classification, the following two-digit occupations are included: 52, "employés civils et agents de la fonction publique"; 53, "agents de surveillance"; 54, "employés administratifs d'entreprise"; 62, "ouvriers qualifiés de type industriel"; 63, "ouvriers qualifiés de type artisanal"; 64, "chauffeurs"; and 65, "ouvriers qualifiés de la manutention, du magasinage et du transport." Finally, the high-skill group includes managers (in craft, manufacturing or sales), executive and knowledge workers (executives, scientists, engineers), intermediate professions (intermediate professions in administration and sales firms, technicians, foremen). The group covers the following two-digit occupations: 21, "artisans (salariés de leur entreprise)"; 22, "commerçants et assimilés (salariés de leur entreprise)"; 23, "chefs d'entreprise de 10 salariés ou plus (salariés de leur entreprise)"; 31, "professions libérales (exercées sous statut de salarié)"; 34, "professeurs, professions scientifiques"; 35, "professions de l'information, des arts et des spectacles"; 37, "cadres administratifs et commerciaux d'entreprises"; 38, "ingénieurs et cadres techniques d'entreprises"; 46, "professions intermédiaires administratives et commerciales des entreprises"; 47, "techniciens"; and 48, "contremaîtres, agents de maîtrise." Finally, we drop the following non-coded occupations: 99, "non codage"; 00, "allocations assedic."

A.3 Total Factor Productivity

In our main results, productivity is calculated using the Levinshon-Petrin estimation technique,[35] with the Ackerberg et al. (2015) correction. We follow Combes et al. (2012) in defining productivity for each firm f and year y as the residual of:

$$ln(V_{fy}) = \beta_{0y} + \beta_1 ln(k_{fy}) + \beta_2 ln(l_{fy}) + \sum_{s=1}^{3} \gamma_s l_{sfy} + \phi_{fy} \tag{A.1}$$

where V_{fy} is value added, k_{fy} is capital, l_{fy} is employment.[36] As in Combes et al. (2012), we distinguish between three skill levels: high, intermediate and low, with l_{sfy} the share of skill level s in the firm's overall employment. We estimate the equation separately for each 2-digit sector.[37] To minimize the impact of outliers, we then winsorize productivity at the 1st and 99th percentile within each of the 6 firm size classes described in Section 2.1.[38] Skill groups are defined in Section A.2.

A.4 Product demand volatility

To compute our measure of demand volatility, we use the EAP survey to recover information on the structure of a firm's product portfolio in a given year:[39]

$$w_{fp,y} = \frac{Sales_{fp,y}}{\sum_{p' \in P_{f,y}} Sales_{fp',y}}$$

where $Sales_{fp,y}$ is the value of product-level sales and $P_{f,y}$ denotes the set of products in the firm's portfolio in year y.[40]

We then leverage upon trade data to construct a time series of the synthetic demand growth that a firm can expect to face, given the structure of its product portfolio in each year:

$$\gamma^{D,P}_{f,t} = \sum_{p' \in P_{f,y}} w_{fp',y} \gamma^{D}_{p',t} \tag{A.2}$$

[35] We use the Stata `prodest` command that exploits the control function approach.

[36] Employment data refers to mean employment and is calculated over the months in each year y.

[37] We focus on 12 2-digit sectors, which include manufacturing, construction, and services (including non-tradables).

[38] Firm size is defined based on the mean employment calculated across months of each year. Productivity percentiles by firm size class are calculated over the 2010-2019 sample. After winsorizing, we further clean the data by only keeping productivity if firm revenues are above the 1st percentile and below the 99th percentile, calculated over the 2010-2019 sample.

[39] The downside is that the use of EAP forces us to focus on a sample of firms in the manufacturing sector, which is not representative of the whole population. See Table B.6 for details.

[40] Each product p is measured at the 4-digit level of the CPA 2008 product nomenclature, which can be merged to Eurostat data as seen below. Sales are constructed following EAP documentation as the sum of *Ventes de produits industriels* (VS2 + VF1 + VF2), *Ventes de services industriels* (VF3 or VT1), *Installation et pose de produits industriels* (IR1 + IR2 + IR3 = IT1), *Réparation et maintenance* (RR1 + RR2 + RR3 = RT1).

where $\gamma^{D}_{p',t}$ is the year-on-year growth of the world demand of product p' recovered from Eurostat trade data at monthly-frequency, where t refers to months of year y.[41] We winsorize this measure at the 1st and 99th percentile of the distribution.

We can finally compute a measure of expected demand volatility:

$$\varepsilon_{f,t} = \sqrt{\frac{1}{2\omega+1}\sum_{\tau=-\omega}^{\omega}(\gamma^{D,P}_{f,t+\tau} - \bar{\gamma}^{D,P}_{f,t})^2} \tag{A.3}$$

In comparison with the baseline measure in eq. (1), the advantage of $\varepsilon_{f,t}$ is that it is a measure of volatility that is orthogonal to the firm's hiring strategy, or the structural churning rate in a particular location. Table A.2 describes the cross-sectional correlation of employment volatility and product demand volatility.

Table A.2: Cross-sectional correlation between employment volatility and product demand volatility

	Dep. Var: log Employment volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
log Product demand volatility	0.039	0.045	0.046	0.026	0.024	0.025
	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
log Age		-0.225	-0.226	-0.221	-0.125	-0.125
		(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
log Productivity			-0.017	-0.020	-0.063	-0.059
			(0.013)	(0.014)	(0.013)	(0.013)
% low-skilled workers						0.110
						(0.027)
Size class FE		✓	✓	✓	✓	✓
Sector FE				✓	✓	✓
Average growth					✓	✓
Adjusted R2	0.001	0.172	0.172	0.177	0.273	0.274

Notes: the table shows the conditional correlation between our baseline measure of idiosyncratic employment volatility (where labor demand year-on-year growth is residualized in the sector×month×year dimensions) and product demand volatility. Each column incrementally controls for the firm's age, productivity, and the % of low-skilled workers (measured in hours). We further control for firm size class fixed effects, sector fixed effects, and for the average firm growth over the 35 consecutive periods used in the calculation of employment volatility, corresponding to $\bar{\gamma}$ in eq. (1). The estimates are based on the sample of 17,423 firms in January 2015 that have non-missing information on product demand volatility. The table contains OLS coefficients and their estimated robust standard errors in parentheses.

When using the measure of expected demand volatility in the location choice model, we additionally impose the condition that the structure of the firm's portfolio is measured at the time of the location decision. We thus use information on the firm's portfolio of products

[41] World demand refers to imports of European products from all countries in the world excluding France.

observed during the first two years of activity. Likewise, world demand used to construct synthetic demand growth is based on the 12 months before and including the firm's creation month.

A.5 Sectoral demand volatility

We construct an alternative measure of demand volatility at the firm level using input-output data and sectoral monthly sales data.

Data. We use the confidential 2015 input-output tables from the INSEE for 138 sectors according to the NA A138 industry classification (expanded NACE for French statistical purposes of national accounting).

We were also able to obtain as a courtesy of the INSEE monthly sectoral sales growth rates between 2010-2019 for 89 sectors (according to the NA A129 classification). Sectoral sales are obtained from the aggregation of firm-level sales data recovered from VAT sources. This data excludes sectors such as agriculture, mining, coking and refining, utilities, vehicle retail, hotels and restaurants, FIRE, and NACE sectors with codes > 82. It also excludes "non-commercial" parts of several service sectors that appear in national accounts but not in for-profit private sector data.

After all the necessary mergers of some sectors to match with the 2-digit level of the French sector nomenclature (Nomenclature d'activités française – NAF rév. 2), there are 135 sectors for which we can compute demand shocks originating from 88 downstream sectors.

Monthly sectoral demand shocks and volatility. For each sector, we have a measure of sales growth $\gamma^D_{s,t}$. We then aggregate these time-series using sales shares recovered from the 2015 I-O tables. For each upstream sector s and downstream sector s', we compute the sales shares as follows:

$$w_{ss',y} = \frac{Sales_{ss',y}}{\sum_t Sales_{st,y}}$$

where $Sales_{ss',y}$ is the value of sales to downstream sector s' from firms in sector s during year y, which we recover from the IO tables.

From this, we can construct a measure of the expected demand an establishment from CZ z and sector s can expect in each year:

$$\gamma^{D,S}_{e(s,z),t} = \sum_{s'} w_{ss',y} \gamma^D_{s',t}.$$

In the last stage, we aggregate across establishments of a given firm in a given commuting zone:

$$\gamma^{D,S}_{f(z),t} = \sum_{e \in f} \frac{empl_{e(s,z),t}}{\sum_{e \in f} empl_{e(s,z),t}} \gamma^{D,S}_{e(s,z),t} \tag{A.4}$$

where $empl_{e(s,z),t}$ is (full-time equivalent) employment in establishment e at time t and the summation is over all establishments of a given firm located in the same commuting zone. Finally, we winsorize this measure at the 1st and 99th percentiles. The resulting (employment-weighted) measure of sectoral demand shocks varies across firms through the sectoral composition of a firm's multiple establishments.

We calculate the volatility of sectoral demand from these measures in a similar way to our EAP-based demand measure described in eq. (A.3) of Section A.4. Table A.3 describes the cross-sectional correlation of employment volatility and sectoral demand volatility.

Table A.3: Cross-sectional correlation between employment volatility and sectoral demand volatility

	Dep. Var: log Employment volatility				
	(1)	(2)	(3)	(4)	(5)
log Sectoral demand volatility	0.006	0.030	0.028	0.025	0.040
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log Age		-0.344	-0.348	-0.220	-0.216
		(0.003)	(0.003)	(0.002)	(0.002)
log Productivity			-0.047	-0.056	-0.043
			(0.003)	(0.003)	(0.003)
% low-skilled workers					0.128
					(0.006)
Size class FE		✓	✓	✓	✓
Average growth				✓	✓
Adjusted R2	0.000	0.114	0.115	0.232	0.234

Notes: the table shows the conditional correlation between our baseline measure of idiosyncratic employment volatility (where labor demand year-on-year growth is residualized in the sector×month×year dimensions) and sectoral demand volatility. Each column incrementally controls for the firm's age, productivity, and the % of low-skilled workers (measured in hours). We further control for firm size class fixed effects, and for the average firm growth over the 35 consecutive periods used in the calculation of employment volatility, corresponding to $\bar{\gamma}$ in eq. (1). We do not control for sector fixed effects as these absorb most of the variation in sectoral demand volatility, which, for most firms captures sectoral demand variations, with the exception of firms with multiple establishments within the same CZ but in different sectors. The estimates are based on the sample of 264,437 firms in January 2015 that have non-missing information on sectoral demand volatility. In terms of sectors, we focus on manufacturing and business services (dropping agriculture, the public sector, finance and insurance, production and distribution of energy and waste, and other services). We also drop accommodation and food services (sectors 55 and 56 in the Nomenclature d'activités française – NAF rév. 2) and real estate (sector 68). The table contains OLS coefficients and their estimated robust standard errors in parentheses.

To estimate local projections, we build a monthly panel dataset of sectoral demand shocks between consecutive months, thus focusing on the synthetic demand *growth* that a firm can expect to face, given its sector and its multiplant composition, if any.

A.6 Control variables for intermediate demand and supply in different locations

We build measures of CZ attractiveness for firms from a particular sector used as controls for the location choice model. To this end, we construct Balassa indices of revealed comparative advantage of each CZ as a location destination. We consider two measures: (i) a proxy for access to downstream demand in a CZ; (ii) a proxy for access to upstream suppliers. In the following, sectors are defined at the 2-digit level of the French sector nomenclature (Nomenclature d'activités française – NAF rév. 2).

Proxy for downstream demand in a CZ. We define the revealed comparative advantage in downstream demand in sector i and CZ k ($RCA\_dem_{i,k}$) as

$$RCA\_dem_{i,k} = \frac{\frac{demand_{i,k}}{demand_k}}{\frac{demand_i}{demand}}$$

where *demand* is nationwide intermediate demand from all sectors in the I-O tables, and $demand\_i$ is nationwide downstream demand for industry i. The ratio in the denominator thus measures how large a sector i is in the demand for input purchases of all firms in France. The numerator computes the importance of sector i in input purchases of firms located in CZ k. Thus, $demand_{i,k}$ is the downstream demand for intermediates produced by a sector i from firms located in CZ k and $demand_k$ is the overall downstream demand of firms in CZ k.

In the absence of direct information on IO linkages by CZ, we approximate $demand_{i,k}$ and $demand_k$, taking into consideration the sectoral structure of employment in CZ k. Aggregating across firms within a CZ and sector, we observe employment at the sector j and CZ k level $emp_{j,k}$. Let S_{ij} be the value of intermediate sales from industry i to j obtained from the nationwide I-O tables (Note that $\sum_j S_{ij} = demand_i$). Our assumption is that the share of S_{ij} originating from CZ k is proportional to employment $emp_{j,k}$, i.e.:

$$demand_{i,k} = \sum_{j=1}^{n} \left(S_{ij} \frac{emp_{j,k}}{emp_j} \right)$$

We observe that for so defined variables

$$\sum_k demand_{i,k} = \sum_k \sum_{j=1}^{n} \left(S_{ij} \frac{emp_{j,k}}{emp_j} \right) = \sum_{j=1}^{n} S_{ij} \sum_k \left(\frac{emp_{j,k}}{emp_j} \right) = \sum_j S_{ij} = demand_i$$

and

$$demand_k = \sum_i demand_{i,k} = \sum_i \sum_{j=1}^{n} \left(S_{ij} \frac{emp_{j,k}}{emp_j} \right) = \sum_{j=1}^{n} \frac{emp_{j,k}}{emp_j} \left(\sum_i^{n} S_{ij} \right)$$

so $demand_k$ is a sum of intermediate downstream sector purchases weighted by their employment in a CZ relative to their national industry employment.

Finally, the ratio of $demand_{i,k}$ over $demand_k$ measures how important the demand of input purchases addressed to sector i by firms in CZ k is, which we normalize by the nationwide equivalent to measure how good CZ k is in terms of access to downstream customers of firms in industry i.

Proxy for upstream supply in a CZ. We similarly define $RCA\_supply_{i,k}$ for upstream supply to industry i in CZ k:

$$RCA\_supply_{i,k} = \frac{\frac{supply_{ik}}{supply_k}}{\frac{supply_i}{supply}}$$

where

$$\begin{aligned}
supply_{i,k} &= \sum_{j=1}^{n} \left(S_{ji} \frac{emp_{j,k}}{emp_j} \right) \\
supply_k &= \sum_i supply_{i,k} = \sum_{j=1}^{n} \frac{emp_{j,k}}{emp_j} \left(\sum_i^n S_{ji} \right) \\
supply_i &= \sum_k supply_{i,k} = \sum_{j=1}^{n} S_{ji} \\
supply &= \sum_i supply_i
\end{aligned}$$

As before, S_{ji} is directly sourced from nationwide IO tables and measures the value of input purchases originating from sector j by firms in sector i. Summing across origin sectors is the value of input purchases by sector i ($supply_i$). The ratio of $supply_i$ over $supply$ measures how important sector i is as a destination of input purchases. The RCA ratio compares this nationwide ratio to the CZ-specific equivalent, as a measure of how easy it is for the typical firm from sector i locating in CZ k to get access to local input purchases.

B Additional Results

B.1 Descriptive statistics

Table B.1: Variance decomposition of employment growth

	R-Squared	Number of FE
Month by year FE	0.6%	72
Month by year by sector FE	1.7%	4,248
Month by year by CZ and month by year by sector FE	1.9%	24,408
Month by year by CZ by sector FE	4.6%	675,620
Firm FE	13.6%	316,041
Number of observations	22,522,922	

Notes: Decomposition of year-on-year employment growth to approximate variance contributions (with R^2). The sample corresponds to the 2012-2017 monthly panel of all firms observed in the January 2015 cross section. The first four rows correspond to separate OLS regressions where year-on-year employment growth is regressed on an increasing number of fixed effects: (i) month by year FE; (ii) month×year×sector FE; (iii) month×year×CZ FE and month×year×sector FE; (iv) month×year×CZ×sector FE. Finally, in the last row, we compute the R-squared obtained from controlling for firm FE.

Table B.2: Firm employment volatility: Correlation with alternative measures

	Workers	Hours	Hours per empl.
Baseline	-	.9038	.4315
Non-residualized volatility	.9990	.9036	.4322
Residualized by sector × month and CZ × month	.9999	.9037	.4314
Month-on-month growth rates	.6799	.6484	.4646
Growth of permanent contracts	.7508	.6883	.3777

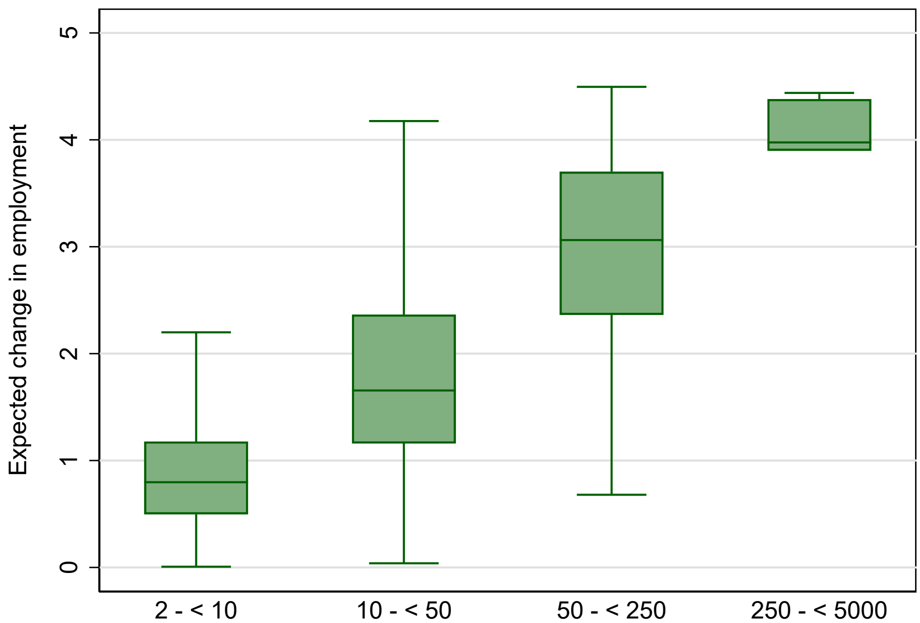
Notes: Correlation coefficients based on various measures of volatility. All measures are computed from the January 2015 cross-section of firms. The baseline measure of idiosyncratic employment volatility is described in section 2.1. The "non-residualized volatility" measure is computed as in equation (1) using the growth rate observed in the data instead of focusing on the idiosyncratic component of growth. The measure which is "residualized by sector×month and CZ×month" is constructed from the residual of an equation that includes CZ×period fixed effects. The "month-on-month growth rates" measure is computed exactly as the baseline except that the raw data are month-on-month (instead of year-on-year) growth rates. Finally, the "growth of permanent contracts" measure is constructed as the baseline on the restricted set of the firm's permanent contracts (CDI). All correlations are statistically significant at the 1% level.

Table B.3: Firm employment volatility: Summary statistics

	Workers		Hours		Hours per empl.	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Baseline	0.207	0.220	0.081	0.178	0.201	0.072
Non-residualized volatility	0.206	0.218	0.081	0.179	0.201	0.073
Residualized by sect×month and CZ×month	0.207	0.220	0.081	0.178	0.200	0.072
Month-on-month growth rates	0.078	0.080	0.024	0.055	0.056	0.016
Growth of permanent contracts	0.205	0.220	0.081	0.185	0.205	0.077

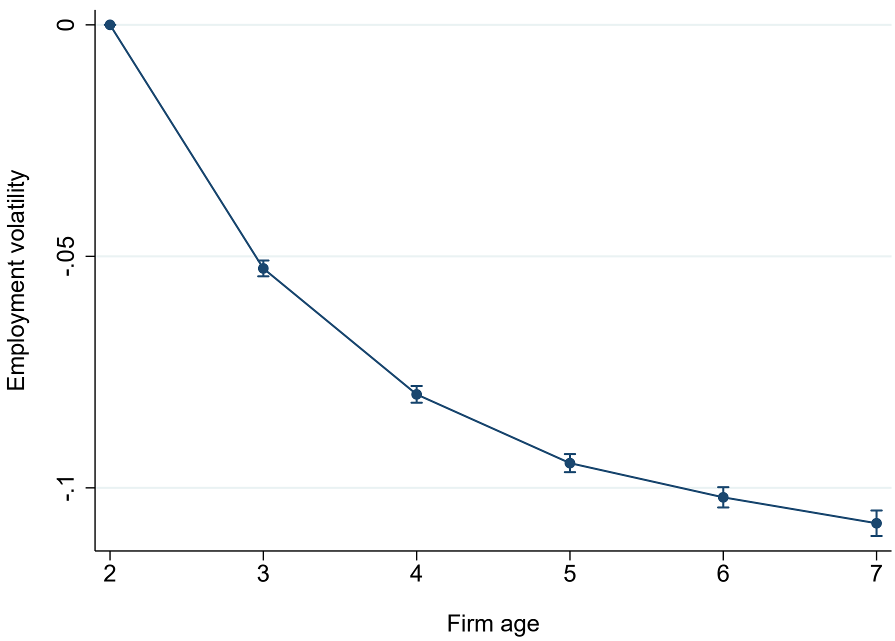
Notes: The statistics are recovered from the cross-section of firms active in January 2015. The baseline measure of idiosyncratic employment volatility is described in section 2.1. The "non-residualized volatility" measure is computed as in equation (1) using the growth rate observed in the data instead of focusing on the idiosyncratic component of growth. The measured which is "residualized by sector×month and CZ×month"is constructed from the residual of an equation that includes CZ×period fixed effects. The "month-on-month growth rates" measure is computed exactly as the baseline except that the raw data are month-on-month (instead of year-on-year) growth rates. Finally, the "growth of permanent contracts" measure is constructed as the baseline on the restricted set of the firm's permanent contracts (CDI).

Figure B.1: Firm employment volatility: Interpretation



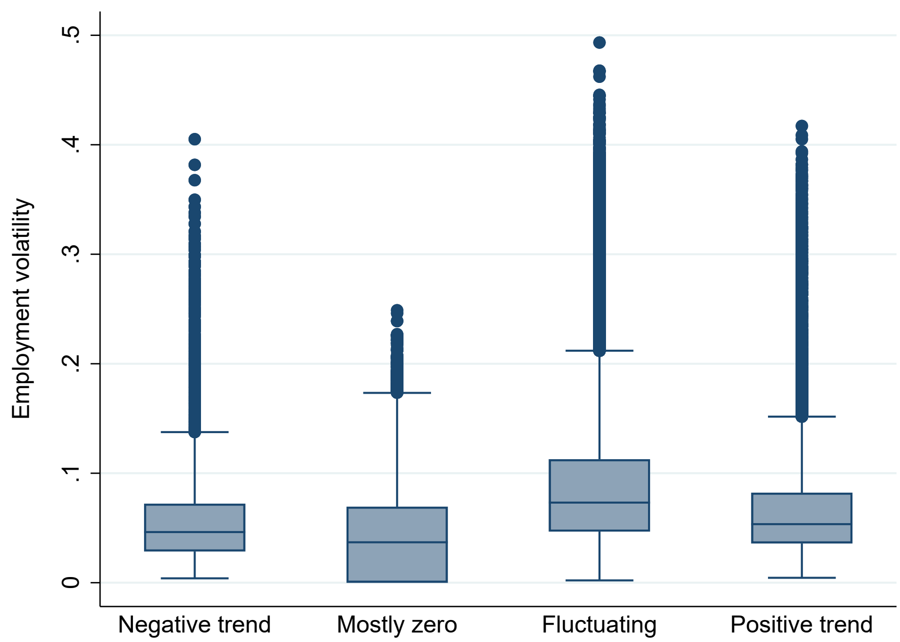
Notes: The figure is based on the January 2015 cross section of single-plant firms. The variable of interest is the expected change in employment computed as the product of the firm's average size and volatility: $(L_{f,t}(1+\gamma_{f,t}+\sigma_{f,t}) - L_{f,t}(1+\gamma_{f,t}-\sigma_{f,t}))/2)$. Results are winsorized at the top 95th percentile.

Figure B.2: Firm employment volatility: The effect of age



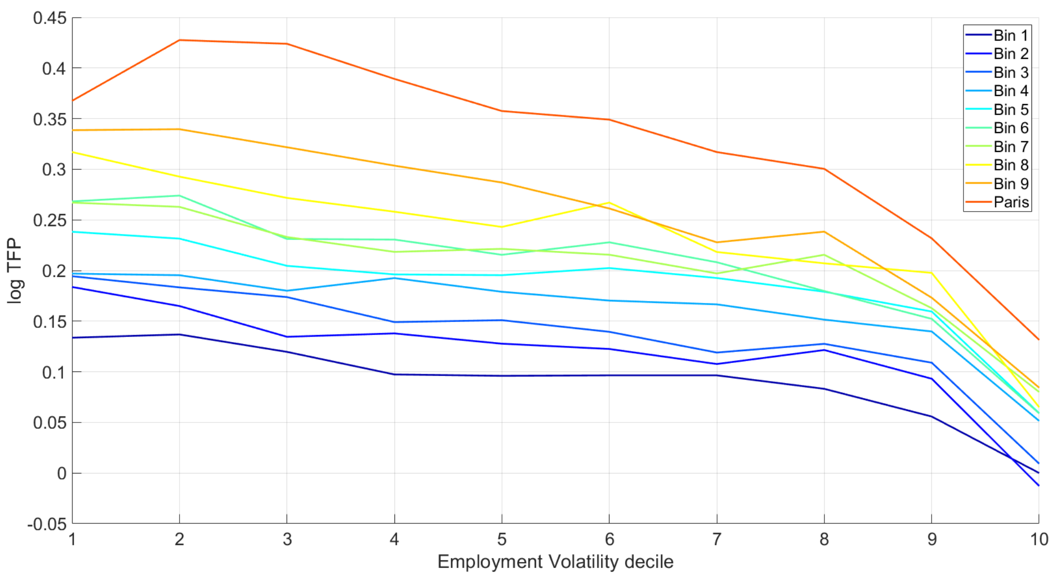
Notes: The figure is based on the panel of firms existing in January 2015, with non-missing employment volatility and that we observe from their creation (115,255 firms, for a total number of observations of $N = 307,167$). The figure plots age fixed effects from a regression of log idiosyncratic employment volatility on age and firm FEs. The reference age category is two years, because volatility is computed over a 35-month window around the date of observation. Whiskers indicate 95% confidence intervals.

Figure B.3: Employment volatility by growth trend



Notes: The figure is based on the January 2015 cross section of single-plant firms (316,041 firms) and displays the distribution of month-on-month employment volatility for firms with different trends of employment growth. Firms with mostly zero growth are defined as having more than 90% zero monthly growth rate over the 35-month interval around January 2015; firms with negative trend growth are those with more than 50% negative monthly growth rates over over the same period; firms with positive trend growth are those with more than 50% positive monthly growth rates; and firms with fluctuating growth rates identify all remaining firms.

Figure B.4: Employment volatility and average productivity, along the distribution of density



Notes: This figure is the 2-dimensional version of Figure 2 in the idiosyncratic employment volatility — log productivity plane by each of the density categories. Density categories include Paris and 9 bins sorted by increasing CZ density. Productivity is conditional on the following firm characteristics: sector, size class, firm age and firm average growth of employment. The estimated equation includes the log density of the commuting zone where the firm is located, log employment volatility, and the interaction of log density and log employment volatility. Idiosyncratic volatility is measured by the standard deviation of the firm's labor demand growth, residualized in the sector×month×year dimensions. Data is based on the January 2015 cross section of firms.

B.2 The hiring advantage of large cities: robustness

We assess the robustness of the correlation shown in Panel A of Figure 3 to several considerations. First, Table B.4 shows that the correlation is robust to controlling for characteristics of the population of the CZ correlated with density and even region fixed effects. CZ with a younger population (resp., a more high-skilled workforce, as measured by the share of managers) are associated with easier (resp., less easy) hiring. The effect of these characteristics is large; however, it does not affect the correlation with log Density. Similarly, controlling for region fixed effects does not affect the correlation, even if dense CZ tend to cluster within dense regions.

Table B.4: Hiring: robustness to other CZ characteristics

	Dep. Var: CZ FE		
	(1)	(2)	(3)
log Density	0.011	0.012	0.012
	(0.003)	(0.004)	(0.004)
Share young		0.406	0.411
		(0.170)	(0.145)
Share managers		-0.208	-0.116
		(0.084)	(0.077)
Region FE			✓
Adjusted R2	0.042	0.067	0.404

Notes: The table shows the correlation between CZ FE from Panel A of Figure 3 and other CZ characteristics ($N = 280$). There are 12 administrative regions in France, but we group CZs spanning multiple regions in the region where the largest share of the CZ population resides. The share of young population in each CZ is defined as the shae of the population aged 15 to 24. The table contains OLS coefficients and their estimated standard errors in parentheses.

In order to better control for firm-level characteristics, we turn to the 2023 BMO survey, for which we have access to information at the establishment level. Out of the 404,877 establishments that answered the survey, 146,724 posted at least one vacancy in 2023. We compute the share of easy expected hires as the ratio of the number of vacancies that are not expected to be difficult to fill to the total number of opened vacancies. On average, this share is equal to 40%. In a first stage, we regress this share on various establishment-level characteristics, including CZ fixed effects (using sampling weights). Then, we correlate the resulting CZ FE estimates with the log density of the working-age population in 2015. The results are displayed in Table B.5. In Column (1), we only regress our index of easy hiring on CZ FE. In Column (2), we control for plant size (in eight classes) and 3-digit sector. In Column (3), we also control for 21 variables that describe the share of posted vacancies by family of jobs as well as the log total number of posted vacancies. These richer specifications increase the explanatory power of the first stage, but leave the correlation between CZ FE and log Density virtually unaffected and very similar to the number represented in Figure 3, Panel A. In Columns (4) and (5), we restrict the sample to establishments that belong to multi-establishment firms. Multi-establishment firms are less subject to hiring difficulties (the share of easy hires is 50% in these establishments, against 37% in single-establishment firms) and they may be able to implement more sophisticated hiring strategies by reshuffling labor across space. Column (4) shows that the correlation is slightly higher, which could suggest a more efficient sorting of vacancies along the density dimension. More interestingly, on this selected sample, we can control for firm FE, as we do in Column (5). Controlling for firm FE dramatically increases the explanatory power of the first stage because establishments that belong to the same firm are likely to experience similar hiring difficulties. However, the correlation between log Density and within-firm hiring difficulties remains very stable, thereby suggesting that this correlation is not purely driven by firm selection.[42]

Table B.5: Hiring: robustness to establishment-level controls

	Dep. Var: CZ FE				
	(1)	(2)	(3)	(4)	(5)
log Density	0.014	0.011	0.011	0.022	0.014
	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)
Adjusted R2	0.035	0.025	0.024	0.029	0.016
Controls First stage					
CZ FE	✓	✓	✓	✓	✓
Size and Industry FE		✓	✓	✓	✓
Plant-level Controls			✓	✓	✓
Firm FE					✓
Adjusted R2 first stage	0.014	0.104	0.121	0.206	0.664
N. first stage	146,724	146,708	146,708	37,839	37,839

Notes: The table shows the correlation between CZ FE and CZ log density ($N = 280$), following a regression at the plant level of the share of easy-to-fill vacancies as a function of CZ fixed effects and an increasingly large set of controls. The table contains OLS coefficients and their estimated standard errors in parentheses. Source: BMO 2023 and Census 2015 for log Density.

[42] We also used an alternative measure of hiring difficulties: a dummy variable equal to 1 if the establishment declares that at least one of the vacancies will be easy to fill. Results are very similar.

B.3 Location choice: samples and robustness

Table B.6: Characteristics of firms in CLM product demand sample

	Mean	Std. dev.	Q1	Median	Q3
Characteristics of firms					
log Productivity	3.12	0.66	2.83	3.16	3.49
log Volatility	-2.59	0.51	-2.87	-2.63	-2.28
% low-skilled workers	17.64	27.90	0.00	0.00	26.54
Firm size upon creation	18.75	36.60	2.00	5.04	18.22
Characteristics of chosen CZ					
Density	632.78	1753.20	59.27	115.11	246.78
% managers	14.70	7.54	9.68	11.96	17.42
% college graduates	21.81	6.42	16.97	20.30	25.44
% active population	72.06	2.78	70.37	71.92	74.09
% unemployed	11.42	2.57	9.70	11.00	12.77
Downstream demand	1.32	0.89	0.88	1.11	1.45
Upstream supply	1.31	0.96	0.87	1.05	1.37

Notes: The product demand sample is based on all firm entries from January 2010 to December 2019 with documented product demand volatility, for a total of 1,682 firm entries.

Table B.7: Characteristics of firms in CLM sectoral demand sample

	Mean	Std. dev.	Q1	Median	Q3
Characteristics of firms					
log Productivity	3.39	0.78	3.01	3.44	3.85
log Volatility	-5.60	1.09	-6.18	-5.29	-4.82
% low-skilled workers	28.56	37.44	0.00	0.00	56.10
Firm size upon creation	5.53	9.62	2.56	3.46	5.46
Characteristics of chosen CZ					
Density	1751.40	2945.99	103.44	233.73	1053.81
% managers	20.60	10.58	12.05	17.32	27.18
% college graduates	27.41	7.74	21.08	26.11	33.99
% active population	73.34	2.75	71.55	73.58	75.83
% unemployed	12.82	2.37	11.55	12.71	13.74
Downstream demand	1.07	0.40	0.87	1.02	1.20
Upstream supply	1.06	0.38	0.86	1.00	1.16

Notes: The sectoral demand sample is based on all firm entries from January 2010 to December 2019 with documented Input-Output demand volatility, for a total of 56,096 firm entries.

Table B.8: Number of firms by sector in CLM samples

	Product demand sample	Sectoral demand sample
Commerce	12	13,632
Construction	10	18,818
Information and communication	1	3,421
Manufacturing of electric and electronics	262	313
Manufacturing of food and beverages	2	2,152
Manufacturing of other industrial products	1,302	2,576
Manufacturing of transport materials	83	81
Professional activities	10	11,330
Transport and logistics	0	3,773
Total	1,682	56,096

Notes: The product demand sample is based on all firm entries from January 2010 to December 2019 with documented product demand volatility. The sectoral demand sample is based on all firm entries from January 2010 to December 2019 with documented Input-Output demand volatility. Sectors are defined based on the standard A17 classification of the Nomenclature d'activités française – NAF rév. 2.

Table B.9: Results of the location choice model: Robustness

	Dependent Variable: CZ choice									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Product demand volatility									
CZ Density M	0.319	0.319	0.604	0.604	0.268	0.268	0.385	0.385	n.a.	n.a.
	(0.033)	(0.033)	(0.020)	(0.020)	(0.032)	(0.032)	(0.031)	(0.031)		
- $\times$ Productivity	0.069	0.054	0.070	0.055	0.070	0.058	0.071	0.057		
	(0.017)	(0.031)	(0.017)	(0.031)	(0.016)	(0.028)	(0.016)	(0.030)		
- $\times$ Volatility	0.030	0.015	0.032	0.017	0.043	0.031	0.033	0.020		
	(0.018)	(0.031)	(0.017)	(0.031)	(0.015)	(0.028)	(0.017)	(0.030)		
- $\times$ Volatility $\times$ Productivity		0.024		0.022		0.018		0.021		
		(0.040)		(0.040)		(0.035)		(0.039)		
Pseudo R2	0.058	0.058	0.049	0.049	0.046	0.046	0.048	0.048		
N. observations	471K	471K	471K	471K	471K	471K	471K	471K		
	Panel B: Sector demand volatility									
CZ Density M	0.510	0.510	0.954	0.954	0.505	0.505	0.650	0.650	0.382	0.382
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)
-$\times$ Productivity	0.059	0.051	0.061	0.052	0.073	0.063	0.073	0.062	0.047	0.036
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)
-$\times$ Volatility	0.022	0.015	0.022	0.013	0.039	0.029	0.029	0.020	0.018	0.008
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
-$\times$ Volatility $\times$ Productivity		0.012		0.014		0.017		0.018		0.017
		(0.005)		(0.006)		(0.006)		(0.004)		(0.005)
Pseudo R2	0.183	0.183	0.167	0.167	0.180	0.180	0.156	0.156	0.185	0.185
N. observations	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M	15.7M
No CZ characteristics			✓	✓						
No Localization economies					✓	✓				
No firm FE							✓	✓		
CZ Density M $\times$ Sector									✓	✓

Notes: Replication of columns (4) and (6) of Table 5 with alternative specifications. Columns (1) and (2) correspond to our baseline specifications. In Columns (3) and (4), we do not control for other characteristics correlated with CZ density: unemployment rate, labor force participation, share of managers among workers and share of college graduates among residents. In Columns (5) and (6) we do not controls for measures of intermediate demand and supply. In Columns (7) and (8) we do not control for firm fixed effects and estimate a simple logit model, controlling for relevant firm specific variables (productivity, volatility and their interaction). In Columns (9) and (10), we allow for differential effect of density by firms' sector, by controlling for the interaction between aggregate sector dummies (in six categories: commerce, construction, information and communication, manufacturing, professional activities, and transport and logistics) and log density. This last test cannot be performed on the EAP sample, where almost all firms belong to the manufacturing sector (see Appendix Table B.8).

Table B.10: Results of the location choice model controlling for characteristics of workers

	Dependent Variable: CZ choice				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Product demand volatility				
CZ Density M	0.319	0.347	0.349	0.347	0.349
	(0.033)	(0.035)	(0.035)	(0.035)	(0.035)
- × Productivity	0.069	0.069	0.061	0.069	0.061
	(0.017)	(0.017)	(0.019)	(0.017)	(0.019)
- × Volatility	0.030	0.029	0.028	0.032	0.032
	(0.018)	(0.017)	(0.018)	(0.019)	(0.019)
- × % low-skilled workers		-0.172	-0.184	-0.172	-0.185
		(0.083)	(0.087)	(0.083)	(0.087)
- × Productivity × % low-skilled workers			0.059		0.062
			(0.067)		(0.069)
- × Volatility × % low-skilled workers				-0.027	-0.035
				(0.115)	(0.120)
Obs.	471K	471K	471K	471K	471K
Pseudo R2	0.058	0.058	0.058	0.058	0.058
	Panel B: Sector demand volatility				
CZ Density M	0.510	0.521	0.521	0.523	0.522
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
- × Productivity	0.059	0.057	0.062	0.058	0.062
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
- × Volatility	0.022	0.019	0.019	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
- × % low-skilled workers		-0.041	-0.044	-0.024	-0.028
		(0.008)	(0.008)	(0.008)	(0.008)
- × Productivity × % low-skilled workers			-0.028		-0.026
			(0.008)		(0.009)
- × Volatility × % low-skilled workers				0.069	0.068
				(0.008)	(0.008)
Obs.	15.7M	15.7M	15.7M	15.7M	15.7M
Pseudo R2	0.183	0.184	0.184	0.184	0.184
CZ characteristics	✓	✓	✓	✓	✓
Intermediate demand and supply	✓	✓	✓	✓	✓

Notes: Coefficient estimates from a conditional logit model with firm fixed effects. Panel A: The sample is based on all firm entries from January 2010 to December 2019 (1,682 entries, resulting in $N = 470,960$ observations) with documented product demand volatility. Panel B: The sample is based on all firm entries from January 2010 to December 2019 (56,096 entries, resulting in $N = 15,706,880$ observations) with documented Input-Output demand volatility. M is the log of CZ density, volatility is the standardized value of expected demand volatility, and productivity is the standardized value of productivity. Standardization is done by year of creation. Column (1) replicates column (4) of Table 5. Columns (2) to (5) introduce the share of low-skilled workers (measured in hours) in the firm's workforce during its first two years of operation. Standard errors in parentheses.

C Theory

C.1 Model set-up and preliminary results

Expected profits — Expected profits upon entry are given by:

$$\mathbb{E}_B(\phi,\varepsilon,M) = \frac{\mu(M)[\phi - R(M)] - c(\delta + r)}{r[r+\delta+\mu(M)]} \tag{C.1}$$

$$\mathbb{E}_W(\phi,\varepsilon,M) = \frac{1}{2} \times \frac{(r+\delta+2\xi)\{\mu(M)[\phi - R(M)] - c(r+\delta)\} + \mu(M)(r+\delta)\varepsilon\phi}{r[(r+\delta)(r+\delta+2\xi) + \mu(M)(r+\delta+\xi)]} \tag{C.2}$$

$$\mathbb{E}_C(\phi,\varepsilon,M) = \frac{1}{2} \times \frac{\mu(M)[\phi(1+\varepsilon) - R(M)] - c(r+\delta+\xi)}{r[r+\delta+\xi+\mu(M)]} \tag{C.3}$$

These three expressions are increasing in ϕ. In addition, we can show that:

$$\frac{\partial \mathbb{E}_B(\phi,\varepsilon,M)}{\partial\phi} - \frac{\partial \mathbb{E}_W(\phi,\varepsilon,M)}{\partial\phi} = \frac{(r+\delta)\mu(M)[(1-\varepsilon)(r+\delta+\mu(M)) + 2\xi]}{2r(r+\delta+\mu(M))[(r+\delta)(r+\delta+2\xi) + (r+\delta+\xi)\mu(M)]} > 0$$

$$\frac{\partial \mathbb{E}_W(\phi,\varepsilon,M)}{\partial\phi} - \frac{\partial \mathbb{E}_C(\phi,\varepsilon,M)}{\partial\phi} = \frac{\xi\mu(M)[(1-\varepsilon)(r+\delta+\mu(M)+2\xi]}{2r(r+\delta+\xi+\mu(M))[(r+\delta)(r+\delta+2\xi) + (r+\delta+\xi)\mu(M)]} > 0$$

Selection cutoffs — Solving for $\mathbb{E}_s(\phi,\varepsilon,M) = 0$ we find:

$$\phi_B(\varepsilon,M) = \phi_B(M) = R(M) + \frac{c(r+\delta)}{\mu(M)} \tag{C.4}$$

$$\phi_W(\varepsilon,M) = \left(\frac{r+\delta+2\xi}{(1+\varepsilon)(r+\delta)+2\xi}\right)\phi_B(M) \tag{C.5}$$

$$\phi_C(\varepsilon,M) = \frac{1}{1+\varepsilon}\left(\phi_B(M) + \frac{c\xi}{\mu(M)}\right) \tag{C.6}$$

Note that $\phi_B(M) \geq \phi_W(M)$ and $\phi_C(\varepsilon,M) \leq \phi_W(M) \iff \varepsilon \geq \tilde{\varepsilon}(M)$, with $\tilde{\varepsilon}(M) = \frac{c(r+\delta+2\xi)}{c(r+\delta)+2\mu(M)R(M)}$.

Switching cutoffs — Solving for $\mathbb{E}_B(\phi,\varepsilon,M) = \mathbb{E}_W(\phi,\varepsilon,M)$ and $\mathbb{E}_W(\phi,\varepsilon,M) = \mathbb{E}_C(\phi,\varepsilon,M)$, we find:

$$\phi_{BW}(\varepsilon,M) = \left(\frac{r+\delta+\mu(M)+2\xi}{(1-\varepsilon)(r+\delta+\mu(M))+2\xi}\right)\phi_B(M) \tag{C.7}$$

$$\phi_{WC}(\varepsilon,M) = \frac{R(M)(r+\delta+2\xi+\mu(M))}{(1-\varepsilon)(r+\delta+\mu(M))+2\xi} \tag{C.8}$$

Note that $\phi_{BW}(M) \geq \phi_B(M)$. In addition, we can show that:

$$\phi_{BW}(\varepsilon,M) - \phi_{WC}(\varepsilon,M) = c\left(\frac{(r+\delta)(r+\delta+2\xi) + (r+\delta+\xi)\mu(M)}{\mu(M)[(1-\varepsilon)(r+\delta+\mu(M))+2\xi]}\right) > 0$$

so that strategy W is never adopted when $c = 0$. Conversely, since $\partial\phi_C(\varepsilon,M)/\partial c > 0$ and $\partial\phi_{WC}(\varepsilon,M)/\partial c = 0$, there is maximum value of c above which strategy C is never adopted.

Sorting cutoffs — Solving for $\frac{\partial \mathbb{E}_s(\phi,\varepsilon,M)}{\partial M} = 0$ as a function of ϕ and ε, we find:

$$\phi_B^*(\varepsilon, M) = \phi_B^*(M) = R(M) - c + \tfrac{R'(M)}{\mu'(M)} \left(\tfrac{\mu(M)(r+\delta+\mu(M))}{(r+\delta)}\right) \tag{C.9}$$

$$\phi_W^*(\varepsilon, M) = \tfrac{(r+\delta+2\xi)R(M)-c(r+\delta+\xi)}{(1+\varepsilon)(r+\delta)+2\xi} + \tfrac{R'(M)}{\mu'(M)} \left(\tfrac{\mu(M)[(r+\delta)(r+\delta+2\xi)+(r+\delta+\xi)\mu(M)]}{(r+\delta)[(1+\varepsilon)(r+\delta)+2\xi]}\right) \tag{C.10}$$

$$\phi_C^*(\varepsilon, M) = \frac{1}{1+\varepsilon}\left[R(M) - c + \tfrac{R'(M)}{\mu'(M)} \left(\tfrac{\mu(M)(r+\delta+\xi+\mu(M))}{(r+\delta)}\right)\right] \tag{C.11}$$

$$\varepsilon_W^*(\phi, M) = \frac{1}{\phi}\left[-(c+\phi-R(M)) - \xi\left(\tfrac{c+2(\phi-R(M))}{r+\delta}\right) + \tfrac{R'(M)}{\mu'(M)} \left(\tfrac{\mu(M)[(r+\delta)(r+\delta+2\xi)+(r+\delta+\xi)\mu(M)]}{(r+\delta)^2}\right)\right] \tag{C.12}$$

$$\varepsilon_C^*(\phi, M) = \frac{1}{\phi}\left[-(c+\phi-R(M)) + \tfrac{R'(M)}{\mu'(M)} \left(\tfrac{(r+\delta+\xi+\mu(M))\mu(M)}{r+\delta+\xi}\right)\right] \tag{C.13}$$

Motion laws — At steady state, the measures of firms in each state are constant, for each strategy. We use bold symbols to distinguish these measures from their corresponding values:

$$\text{Strategy B:} \quad \begin{cases} \mu(M)\boldsymbol{V_B}(M) = \delta \boldsymbol{A_B}(M) \\ \boldsymbol{V_B}(M) + \boldsymbol{A_B}(M) = \boldsymbol{B}(M) \end{cases} \tag{C.14}$$

$$\text{Strategy W:} \quad \begin{cases} [\xi + \mu(M)]\boldsymbol{V_W}(M) = \delta \boldsymbol{A_W^h}(M) + \xi \boldsymbol{I_W}(M) \\ \xi \boldsymbol{I_W}(M) = \xi \boldsymbol{V_W}(M) + \delta \boldsymbol{A_W^l}(M) \\ (\delta+\xi)\boldsymbol{A_W^h}(M) = \mu(M)\boldsymbol{V_W}(M) + \xi \boldsymbol{A_W^l}(M) \\ (\delta+\xi)\boldsymbol{A_W^l}(M) = \xi \boldsymbol{A_W^h}(M) \\ \boldsymbol{V_W}(M) + \boldsymbol{I_W}(M) + \boldsymbol{A_W^h}(M) + \boldsymbol{A_W^l}(M) = \boldsymbol{W}(M) \end{cases} \tag{C.15}$$

$$\text{Strategy C:} \quad \begin{cases} [\mu(M) + \xi]\boldsymbol{V_C}(M) = \delta \boldsymbol{A_C}(M) + \xi \boldsymbol{I_C}(M) \\ \xi \boldsymbol{I_C}(M) = \xi[\boldsymbol{A_C}(M) + \boldsymbol{V_C}(M)] \\ (\delta+\xi)\boldsymbol{A_C}(M) = \mu(M)\boldsymbol{V_C}(M) \\ \boldsymbol{V_C}(M) + \boldsymbol{I_C}(M) + \boldsymbol{A_C}(M) = \boldsymbol{C}(M) \end{cases} \tag{C.16}$$

where $\boldsymbol{B}(M)$, $\boldsymbol{W}(M)$ and $\boldsymbol{C}(M)$ are the respective measures of firms that follow strategies B, W and C.

C.2 Proofs

Proof of Proposition 1 — Employment is a random variable that follows a Bernoulli distribution. The variance of employment is thus

$$\sigma^l(\phi, \varepsilon, M^*(\phi, \varepsilon), s^*(\phi, \varepsilon)) = \mathbb{P}(\phi, \varepsilon, M^*, s^*)\left[1 - \mathbb{P}(\phi, \varepsilon, M^*, s^*)\right]$$

where $\mathbb{P}(\phi, \varepsilon, M^*, s^*)$ is the probability of a position being filled, which follows the steady-state constraints given by Equations C.14–C.16 with $\boldsymbol{B}(M) = \boldsymbol{W}(M) = \boldsymbol{C}(M) = 1$. Employment volatility is higher under strategy C than under strategy B if $\xi < (\mu(M) - 2\delta)(\delta + \mu(M))/(2\delta)$, which is only possible if $\mu(M) > 2\delta$, and is more likely to be satisfied if M is large, given $\mu'(M) > 0$.

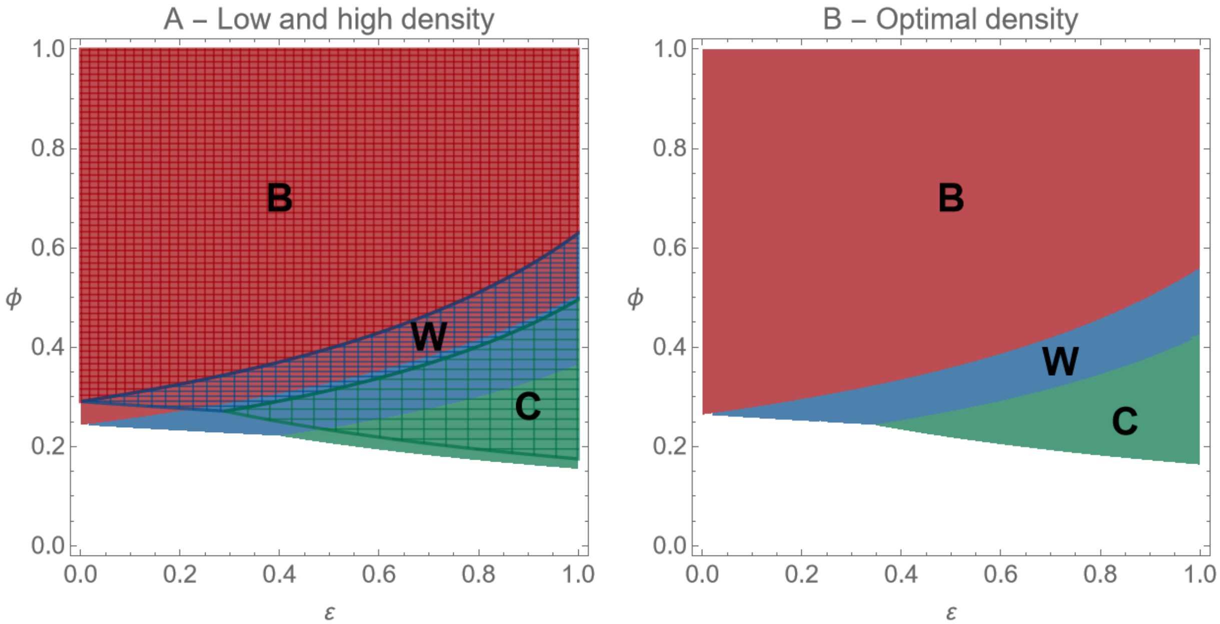
Proof of Proposition 2 — Result 2.1 stems from the facts that $\partial\phi_{WC}(\varepsilon, M)/\partial\varepsilon > 0$ and $\partial\phi_C(\varepsilon, M)/\partial\varepsilon < 0$ and that the selection cutoff for strategy C is the lowest, as long as $\varepsilon \geq \tilde{\varepsilon}(M)$. Result 2.2 stems from the fact that $\partial^2\phi_{WC}(\varepsilon, M)/\partial\varepsilon\partial\varepsilon > 0$.

Proof of Proposition 3 — Result 3.1 is obtained by noticing that, under Assumptions 1 and 2, $\partial\phi_{BW}(\varepsilon, M)/\partial M > 0$. Thus, the area of region B decreases with density. Moreover, under Assumption 2, $\partial\phi_W(\varepsilon, M)/\partial M > 0$. In addition, under no assumption, $\partial[\phi_{BW}(\varepsilon, M) - \phi_{WC}(\varepsilon, M)]/\partial M < 0$. Thus, the area of region W decreases with density. Finally, under no assumption, $\partial\tilde{\varepsilon}(M)/\partial M < 0$. In addition, under Assumption 2, $\partial[\phi_{WC}(\varepsilon, M) - \phi_C(\varepsilon, M)]/\partial M > 0$. Thus, the area of region C increases with density. Result 3.2 can be derived by observing that the productivity-volatility substitution for selection is represented by $\phi_W(\varepsilon, M)$ for $\varepsilon \in [0, \tilde{\varepsilon}(M)]$ and $\phi_C(\varepsilon, M)$ for $\varepsilon \in [\tilde{\varepsilon}(M), 1]$. Then, under Assumption 2, $\partial^2\phi_W(\varepsilon, M)/\partial\varepsilon\partial M < 0$ and $\partial^2\phi_C(\varepsilon, M)/\partial\varepsilon\partial M < 0$. Thus, in denser cities, volatility and productivity are better substitutes for lowering the selection of firms.

Proof of Proposition 4 — Result 4.1 stems from the fact that under Assumption 3, we can show that $\forall s \in \{B, W, C\}, \partial\phi_s^*(\varepsilon, M)/\partial M > 0$ and $\forall s \in \{W, C\}, \partial\varepsilon_s^*(\phi, M)/\partial M > 0$. Therefore, more productive and more volatile firms sort into denser cities. Results 4.2 stems from the fact that $\forall s \in \{W, C\}, \partial^2\phi_s^*(\varepsilon, M)/\partial M\partial\varepsilon < 0$ and $\partial^2\varepsilon_s^*(\phi, M)/\partial M\partial p < 0$. Therefore, more productive (resp., volatile) firms sort into denser cities if they are more volatile (resp., productive). This second result ensures that the share of churning firms increases with density, even though average productivity also increases with density. Then, again under Assumption 3, we can also show that $\forall\varepsilon \in [0, 1], \frac{\partial\phi_B^*(M)}{\partial M} > \frac{\partial\phi_W^*(\varepsilon, M)}{\partial M} > \frac{\phi_C^*(\varepsilon, M)}{\partial M}$. The relationship between productivity and density is stronger when firms choose strategy B, followed by strategy W and then C. Therefore, the productivity-density gradient decreases with volatility, which proves result 4.3.

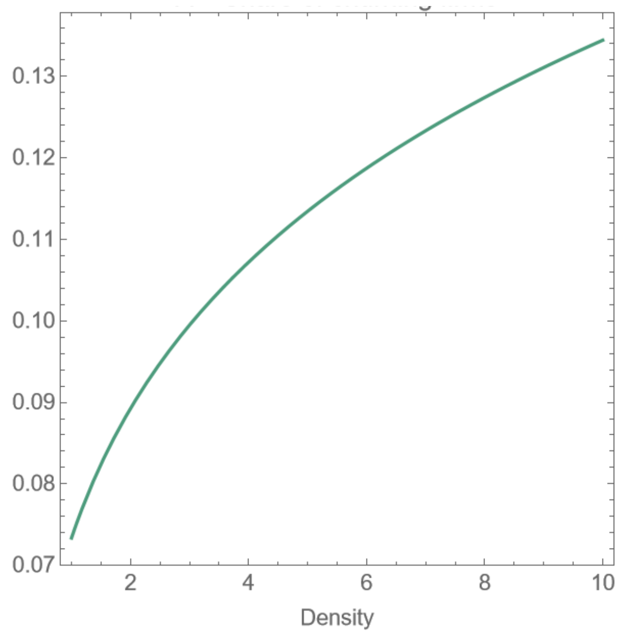
C.3 Additional figures

Figure C.1: Strategy choice and city choice



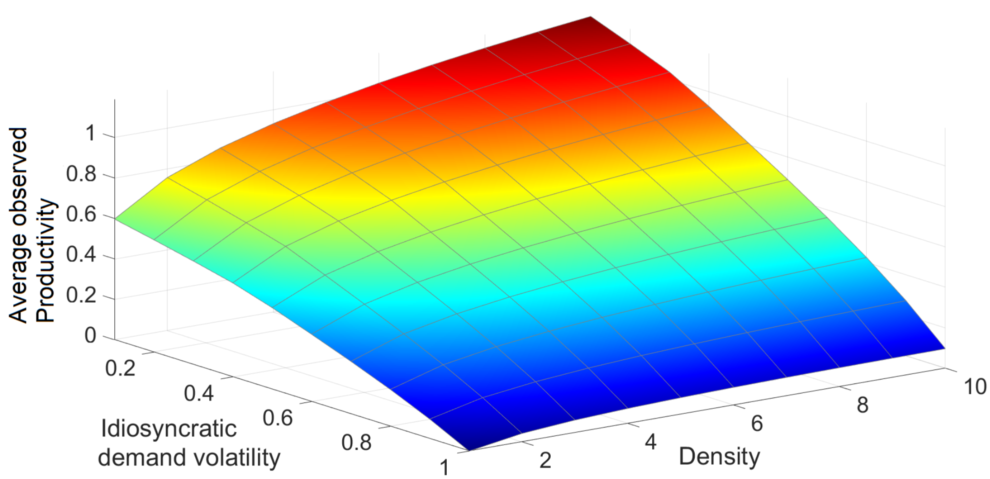
Calibration: $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $c = 0.1$, $\mu(M) = 0.3M^{0.05}$, $R(M) = 0.2M^{0.1}$, $\overline{p} = 1$. Panel A: The figure represents the set of (ε, ϕ) combinations associated with each adopted strategy, for a low density ($M = 1$, plain colors), and for a high density ($M = 10$, mesh lines). The letters locate adopted strategies when $M = 10$. Panel B: The figure represents the set of (ε, ϕ) combinations associated with each adopted strategy, for the optimal level of density, found by numerical search.

Figure C.2: The share of churning firms across space



Calibration: $c = 0.1$, $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $\mu(M) = 0.3M^{0.05}$, $R(M) = 0.2M^{0.1}$, $\overline{p} = 1$. We assume that ϕ and ε are independent and uniformly distributed over $[0, 1]$. The optimum is found by a numerical search. The share of churning firms is given by $\mathcal{C}(M) = \frac{\int\int \mathbf{1}_{C=s^*(\phi,\varepsilon,M)} d\phi d\varepsilon}{\sum_s \int\int \mathbf{1}_{s=s^*(\phi,\varepsilon,M)} d\phi d\varepsilon}$.

Figure C.3: The productivity-density gradient, along the volatility distribution



Calibration: $c = 0.1$, $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $\mu(M) = 0.3M^{0.05}$, $R(M) = 0.2M^{0.1}$, $\overline{p} = 1$. We assume that ϕ and ε are independent and uniformly distributed over $[0, 1]$. The optimum is found by a numerical search. The average productivity of firms is computed in a neighborhood d_ε of the mid-point d of each decile of ε and is given by $\phi^*(M, d) = \frac{\sum_s \int\int_{d_\varepsilon} \mathbf{1}_{s=s^*(\phi,\varepsilon,M)} \phi^*_s(\varepsilon, M) d\phi d\varepsilon}{\sum_s \int\int_{d_\varepsilon} \mathbf{1}_{s=s^*(\phi,\varepsilon,M)} d\phi d\varepsilon}$. For consistency with Figure 2, productivity is shown relative to its value in the tenth decile of volatility and the first decile of density.

C.4 Endogenous matching rate

In order to recover $\boldsymbol{B}(M)$, $\boldsymbol{W}(M)$ and $\boldsymbol{C}(M)$ in eq. (C.14)-(C.16), we introduce an entry process: In each city, we assume that there is a continuum of latent firms with known distribution $h(\phi, \varepsilon)$. Those firms pay a cost f_E to draw (ϕ, ε). Free entry means that:

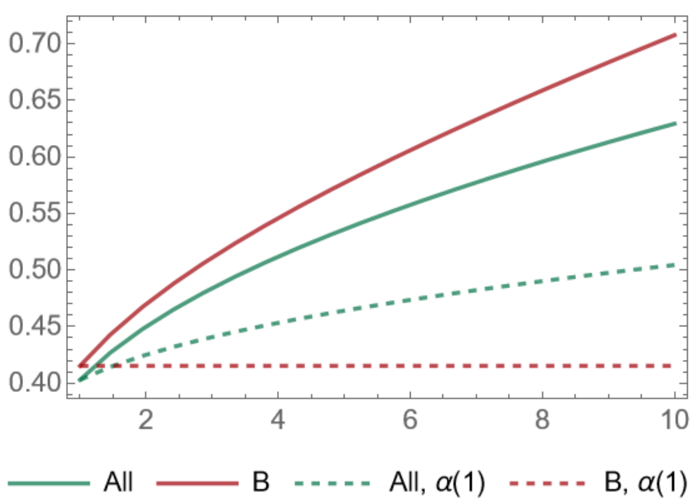
$$\forall M, f_E = \int\int \max\left\{0, \max_s\{\mathbb{E}_s(\phi, \varepsilon, M)\}\right\} h(\phi, \varepsilon) d\phi d\varepsilon \tag{C.17}$$

Market tightness is given by the ratio of the number of vacancies to that of unemployed workers:

$$\theta(M) = \frac{\sum_s \boldsymbol{V_s(M)}}{M - \sum_s \boldsymbol{A_s}(M)} \tag{C.18}$$

If we denote $\alpha(M) = M/F(M)$ with $F(M) = \boldsymbol{B}(M) + \boldsymbol{W}(M) + \boldsymbol{C}(M)$ the density of firms and use a parametric assumption $\mathcal{M}(\cdot)$ on the matching technology, we can solve numerically for the fixed point given by eq. (C.17)-(C.18) and recover the values of $\alpha(M)$ and $\mu(M)$.

Figure C.4: Endogenous worker finding rate



Calibration: $c = 0.1$, $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $R(M) = 0.2M^{0.1}$, $\overline{p} = 1$. We assume that ϕ and ε are independent and uniformly distributed over $[0, 1]$. The value of $\mu(M)$ is obtained as the numerical solution to the fixed point problem described in the text, with a Cobb-Douglas matching technology $\mathcal{M}(V, U) = \sqrt{VU}$ and f_E set to 7.5 so that the resulting unemployment rate lies between 5% and 10%. All: $\mu(M)$ is obtained by solving the full model; B: $\mu(M)$ is obtained by solving the restricted model. Continuous lines mean that firm density adjusts to meet the free entry condition. Dashed lines mean that firm density is set to its equilibrium value when $M = 1$.

We illustrate this method with the same calibration as in the main text. The results are shown in Figure C.4, for two different scenarios: either the full model, where firms may follow any of the three strategies, or a restricted model where firms may only follow the B strategy. Under this parametrization, the impact of density on the worker finding rate is higher under the restricted model: the indirect negative effect of churning through firm entry trumps the direct positive effect. Conversely, even if the number of firms does not adjust, firms that are allowed to churn still benefit from better matching conditions in larger cities. To substantiate this last point, we simulate two counterfactual situations where α is set to its value for the lowest density ($M = 1$): matching economies, as measured by $d\mu(M)/dM$, drop by half when firms are allowed to churn, but they drop to zero when firms are not allowed to churn.

Discussion: the role of the correlation of shocks — In line with our empirical analysis, the previous exercise is based on the assumption that demand shocks affect each firm idiosyncratically. If we were to assume that demand shocks affect all firms simultaneously, the set-up would be slightly different, and so would be the implications of the model in terms of the sorting of firms. For example, in the extreme case where the economy fluctuates between high and low states at an aggregate level, $\mu(M)$ fluctuates too, between a high value in the high state (when all existing firms operate normally) and a lower value in the low state (when low-productivity firms are idle). In the high state, all the firms try to hire at the same time, which exerts a positive pressure on market tightness, thus discouraging the entry of the least productive firms. In the low state, however, high-productivity firms benefit from lower hiring competition. Therefore, if demand shocks are strongly correlated with each other, matching economies do not depend on the sorting of firms according to their volatility, but only according to their productivity, as in existing frameworks displaying labor market pooling externalities.

C.5 Match quality

We extend our base model to discuss the impact of match quality on churning. To that end, we assume that the firm-worker match can either be "good" or "bad" (denoted by a second superscript g or b, respectively). The respective probabilities are given by $\pi(M)$ and $(1-\pi(M))$, with $\pi'(M) > 0$. In a good (resp., bad) match, sales are equal to $\phi(1 \pm \varepsilon) + \alpha$ (resp., to $\phi(1 \pm \varepsilon) - \alpha$), with $\alpha > 0$.[43] The firm decides what to do in the low state of demand, but also when it is faced with a bad match: in particular, it can refuse a bad match, and stay vacant. A strategy s is therefore determined by $W_s(\phi, \varepsilon, M)$ as before, but also by $C_s^b(\phi, \varepsilon, M)$ and $C_s^g(\phi, \varepsilon, M)$ (depending on whether the current match is good or bad), and by $Y_s^t(\phi, \varepsilon, M) \in \{A_s^{tb}(\phi, \varepsilon, M), V_s^t(\phi, \varepsilon, M)\}$ (depending on whether the vacant firm in state t accepts a bad match or not). The value functions associated with strategy s (detailed below) are summarized as follows:

$$
\begin{aligned}
rV_s^h(\phi,\varepsilon,M) &= -c + \mu(M)[\pi(M)A_s^{h,g}(\phi,\varepsilon,M) + (1-\pi(M))Y_s^h(\phi,\varepsilon,M) - V_s^h(\phi,\varepsilon,M)] \\
&+ \xi[W_s(\phi,\varepsilon,M) - V_s^h(\phi,\varepsilon,M)] \\
rV_s^l(\phi,\varepsilon,M) &= -c + \mu(M)[\pi(M)A_s^{l,g}(\phi,\varepsilon,M) + (1-\pi(M))Y_s^l(\phi,\varepsilon,M) - V_s^l(\phi,\varepsilon,M)] \\
&+ \xi[V_s^h(\phi,\varepsilon,M) - V_s^l(\phi,\varepsilon,M)] \\
rA_s^{h,g}(\phi,\varepsilon,M) &= \phi(1+\varepsilon) + \alpha - R(M) + \delta[V_s^h(\phi,\varepsilon,M) - A_s^{h,g}(\phi,\varepsilon,M)] \\
&+ \xi[C_s^g(\phi,\varepsilon,M) - A_s^{h,g}(\phi,\varepsilon,M)] \\
rA_s^{l,g}(\phi,\varepsilon,M) &= \phi(1-\varepsilon) + \alpha - R(M) + \delta[W_s(\phi,\varepsilon,M) - A_s^{l,g}(\phi,\varepsilon,M)] \\
&+ \xi[A_s^{h,g}(\phi,\varepsilon,M) - A_s^{l,g}(\phi,\varepsilon,M)] \\
rA_s^{h,b}(\phi,\varepsilon,M) &= \phi(1+\varepsilon) - \alpha - R(M) + \delta[V_s^h(\phi,\varepsilon,M) - A_s^{h,b}(\phi,\varepsilon,M)] \\
&+ \xi[C_s^b(\phi,\varepsilon,M) - A_s^{h,b}(\phi,\varepsilon,M)] \\
rA_s^{l,b}(\phi,\varepsilon,M) &= \phi(1-\varepsilon) - \alpha - R(M) + \delta[W_s(\phi,\varepsilon,M) - A_s^{l,b}(\phi,\varepsilon,M)] \\
&+ \xi[A_s^{h,b}(\phi,\varepsilon,M) - A_s^{l,b}(\phi,\varepsilon,M)] \\
rI_s(\phi,\varepsilon,M) &= \xi[V_s^h(\phi,\varepsilon,M) - I_s(\phi,\varepsilon,M)]
\end{aligned}
$$

For simplicity, we abstract from the intermediate *wait-and-see* strategy by assuming $c = 0$. Under this assumption, there are five possible strategies. In the B strategy, as in the base model, the firm hires and does not fire in low state. It also accepts both good and bad matches. Conversely, in the B' strategy, the firm only accepts good matches, while still keeping the same strategy for high and low states. In the C strategy, as in the base model, the firm becomes idle in low state. Similarly to the B strategy, there is also a C' strategy whereby the firm churns and does not accept bad matches. Finally, there is an intermediate BC strategy, whereby a good match is shielded against churning: the firm does not hire in low state, but it will only fire its worker in low state if it is in a bad match. These strategies are summarized in Table C.1.

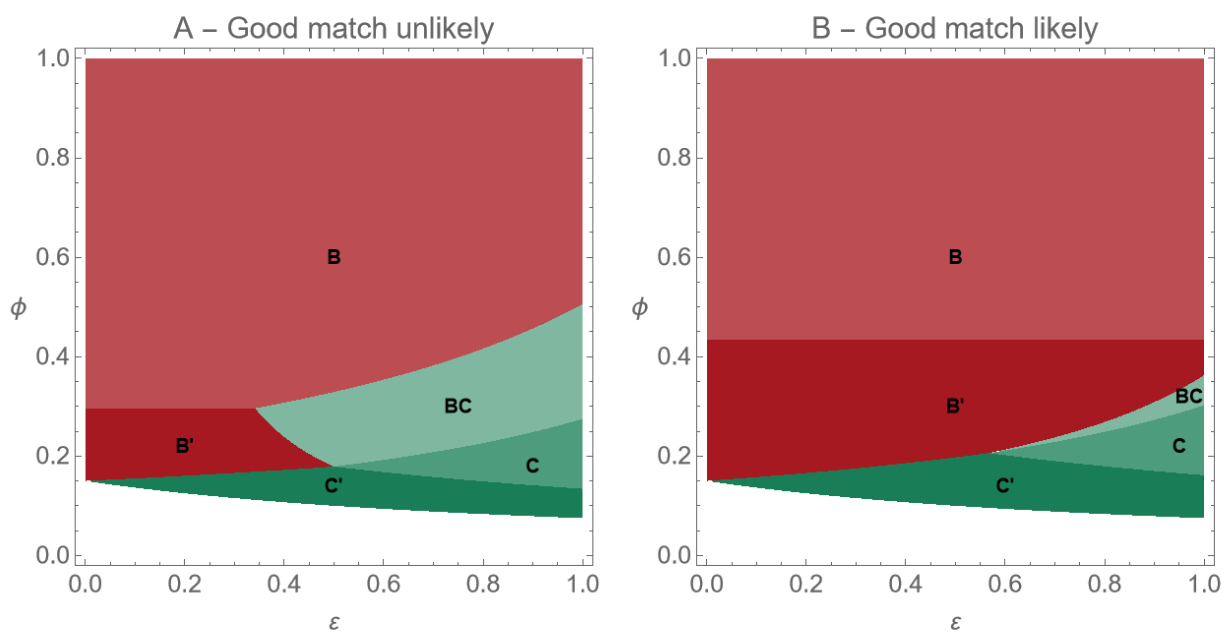
[43] This reduced form expression assumes perfect separability between firm productivity and match productivity. We could alternatively assume that both components are complementary to each other, with, for example, $(1 \pm \alpha)\phi(1 \pm \varepsilon)$, with $\alpha \in [0, 1]$. The conclusions presented here do not depend on this modeling choice.

Table C.1: Strategies and values of low state and bad match

	$W_s(\phi,\varepsilon,M)$	$C_s^b(p,\varepsilon,M)$	$C_s^g(\phi,\varepsilon,M)$	$Y_s^h(p,\varepsilon,M)$	$Y_s^l(p,\varepsilon,M)$
B	$V_B^l(\phi,\varepsilon,M)$	$A_B^{l,b}(\phi,\varepsilon,M)$	$A_B^{l,g}(\phi,\varepsilon,M)$	$A_B^{h,b}(\phi,\varepsilon,M)$	$A_B^{l,b}(\phi,\varepsilon,M)$
B'	$V_{B'}^l(\phi,\varepsilon,M)$	n.a.	$A_{B'}^{l,g}(\phi,\varepsilon,M)$	$V_{B'}^h(\phi,\varepsilon,M)$	$V_{B'}^l(\phi,\varepsilon,M)$
BC	$I_{BC}(\phi,\varepsilon,M)$	$I_{BC}(\phi,\varepsilon,M)$	$A_{BC}^{l,g}(\phi,\varepsilon,M)$	$A_{BC}^{h,b}(\phi,\varepsilon,M)$	n.a.
C	$I_C(\phi,\varepsilon,M)$	$I_C(\phi,\varepsilon,M)$	$I_C(\phi,\varepsilon,M)$	$A_C^{h,b}(\phi,\varepsilon,M)$	n.a.
C'	$I_{C'}(\phi,\varepsilon,M)$	n.a.	$I_{C'}(\phi,\varepsilon,M)$	$V_{C'}^h(\phi,\varepsilon,M)$	n.a.

As in our base model, we can show that regardless of the chosen strategy, high-productivity firms have more to gain from locating in denser areas. The same is true for high-volatility firms that follow strategies C and C'. However, things are more subtle for the intermediate 'partial-churning' strategy BC: if $\pi(M)$ is low, firms in a good match may choose to keep their worker in a low state of demand because they do not want to face the risk of a bad match later on. For this reason, the sign of $\partial^2\mathbb{E}_{BC}(\phi,\varepsilon,M)/\partial\varepsilon\partial M$ is only positive for low enough values of $\pi'(M)$. This pattern is illustrated in Figure C.5, which compares adopted strategies for two different levels of $\pi(M)$. If the probability of a good match is low, the BC strategy can be widely adopted (Panel A); conversely, if this probability is high, the firm is more likely to opt for the non-churning screening strategy B', or for the churning strategies C and C' that help the firm avoid or get rid of a bad match (Panel B).

Figure C.5: Strategy choice and match quality



Calibration: $\xi = 0.2$, $r = 0.03$, $\delta = 0.1$, $c = 0$, $\mu(M) = 0.3$, $R(M) = 0.2$, $\overline{p} = 1$ and $\alpha = 0.05$. Both panels represent the set of (ε,ϕ) combinations associated with each adopted strategy, for a low probability of a good match ($\pi(M) = 0.2$, Panel A) and a high probability ($\pi(M) = 0.8$, Panel B).

C.6 Firm size heterogeneity and demand

In this section, we provide an extension to our base model in the spirit of Melitz (2003), introducing monopolistically competitive firms facing a CES demand system that draw heterogeneous productivity and demand volatility upon entry. This connection allows us to (i) explicitly model demand shocks, (ii) introduce firm size, (iii) clarify the link between productivity thresholds and the share of volatile firms active in a given market and (iv) exhibit that the same forces as used in our parsimonious model are needed to generate the main results of the paper. We use the model to perform comparative statics. All proofs and derivations are available upon request.

Assumptions — We analyze a differentiated goods sector in one city of size M. There are M workers-consumers inelastically providing one unit of labor that spend a fraction γ of their income I on the sector's differentiated goods over which they have CES preferences.

There is a unit mass of potential entrants in each city. Firms pay a fixed entry cost $f_E > 0$ after which they learn their productivity ϕ and demand volatility. Productivity is drawn from a Pareto distribution of shape ν and scale $\phi_{min} > 0$. A proportion χ of firms face constant demand, while $(1-\chi)$ are exposed to volatile demand flows. More specifically, the firm observes the demand for its variety at each period

$$q\left(p,\varepsilon\right) = \varepsilon^{\eta}\bar{Q}p^{-\eta}$$

where $\bar{Q}$ is aggregate real consumption and ε is the firm's idiosyncratic demand.[44] The corresponding indirect demand is $p\left(q,\varepsilon\right) = \varepsilon\left(\bar{Q}\right)^{\frac{1}{\eta}}\left(q\right)^{-\frac{1}{\eta}}$ which allows us to link this extension with the base model in the main paper. For the firms with no demand volatility, we normalize $\varepsilon = 1$. Volatile firms alternate between ε_l and ε_h (respectively low and high demand) at a rate ξ. We consider the case where $\frac{\varepsilon_l+\varepsilon_h}{2} = 1$, i.e. volatile and non-volatile firms only differ by the second-moment of their indirect demand process, conditional on their productivity. In our exposition, we further assume that $\varepsilon_l = 0$ and $\varepsilon_h = 2$. These are extreme values that, however, permit analytical characterization of the problem without resorting to simulations.

In the rest of the model, we assume monopolistic competition, i.e. firms are input price takers and view any aggregate parameters (e.g. labor market tightness, or real consumption) as being exogenous.

Once productivity and volatility are revealed, the firm decides whether to pay a set-up cost $f_p > 0$ to produce, then chooses a hiring strategy. In comparison with the stylized model in Section 3, we concentrate on the two extreme strategies, namely Business-as-usual and Churning, which corresponds to the case where c is small. While the baseline model considers one-job firms, we now consider the firm's decision on a measure of job openings, given an exogenous filling rate $\mu(M)$ and separation rate δ for each of these positions. If a worker fills a position, she produces ϕ units of the differentiated good. The firm assesses the present discounted value (PDV) of each created position given operational and hiring costs, as well

[44] We assume that $\nu > \eta - 1$ to ensure finite aggregate productivity levels.

as the job filling and separation rates. When the firm enters, it doesn't know the state of its demand ε, but it immediately chooses the type of each position it creates. A position is permanent if the firm will not fire the employed worker under any circumstances and only an exogenous separation can destroy it. A position will be a churning one if the firm may also fire workers when demand is low.

Business as usual strategy — Firms using this strategy keep employment constant and hence also production $\bar{q}$ and the associated cost. It is straightforward to show that non-volatile firms always choose this strategy. Volatile firms instead choose between Business-as-usual and Churning. Under Business-as-usual, the firm produces at full capacity and adjusts its price to demand shocks.

The employment level $\bar{L}_B$ chosen by a Business-as-usual firm upon entry, assuming it does not know a priori the state of the demand, maximizes expected profits

$$\Pi_B(\phi, \varepsilon, M) = \left[\frac{\mu(M)\left\{[\frac{p_l+p_h}{2}]\phi - R(M)\right\} - c(\delta + r)}{r[r + \delta + \mu(M)]}\right]\bar{L}_B \tag{C.19}$$

subject to $p_t = \varepsilon_t \left(\bar{Q}\right)^{\frac{1}{\eta}} (\bar{q})^{-\frac{1}{\eta}}$, where t corresponds to the low or high state. $\bar{q} = \phi\kappa_B\bar{L}_B$ is the expected (constant) output given the adopted strategy where $\kappa_B = \frac{\mu(M)}{\delta+\mu(M)}$ is the fraction of time a position is filled. The term under brackets is simply the present discounted value of a permanent position and is as in eq. (C.1) in the baseline model (using the fact that the demand shocks average to one across states), except that now we explicitly allow the firm to optimize on its price p.

Letting $\Gamma_1 = \frac{\mu(M)}{r[r+\delta+\mu(M)]}$ and $\Gamma_2 = \frac{\mu(M)R(M)+c(\delta+r)}{r[r+\delta+\mu(M)]}$, we can rewrite the problem of the firm as

$$\max_{\bar{L}_B}\left[\Gamma_1\left(\frac{\phi\kappa_B\bar{L}_B}{\bar{Q}}\right)^{-1/\eta}\phi - \Gamma_2\right]\bar{L}_B$$

The optimal solution gives

$$\begin{aligned}\bar{L}_B &= \left(\frac{\eta}{\eta-1}\frac{\Gamma_2}{\Gamma_1}\right)^{-\eta}\left(\frac{\bar{Q}}{\kappa_B}\right)\phi^{\eta-1}\\ p_t &= \varepsilon_t\frac{\eta}{\eta-1}\frac{\Gamma_2}{\phi\Gamma_1}\end{aligned}$$

Plugging the equilibrium strategies into eq. (C.21) implies:

$$\Pi_B(\phi, \varepsilon, M) = \frac{\Gamma_2}{\eta-1}\left(\frac{\eta}{\eta-1}\frac{\Gamma_2}{\Gamma_1}\right)^{-\eta}\frac{\bar{Q}}{\kappa_B}\phi^{\eta-1}$$

which does not depend on the firm's volatility.

Churning strategy — Consider now a firm that lays off some workers in the low state of demand. Given the firm faces zero demand in the low state ($\varepsilon_l = 0$), it can be shown that if firing some workers is preferred in the low demand state, the firm would want to fire its entire workforce.[45]

Following the same steps as before, the problem of the firm consists in choosing $\bar{L}_C$ to maximize expected discounted profits:

$$\Pi_C(\phi, \varepsilon, M) = \frac{1}{2}\left[\frac{\mu(M)\{p_h\phi - R(M)\} - c(r+\delta+\xi)}{r[r+\delta+\xi+\mu(M)]}\right]\bar{L}_C \tag{C.20}$$

$$= \frac{1}{2}\left[\Phi_1\varepsilon_h\left(\frac{\phi\kappa_C\bar{L}_C}{\bar{Q}}\right)^{-\frac{1}{\eta}}\phi - \Phi_2\right]\bar{L}_C \tag{C.21}$$

where $\Phi_1 \equiv \frac{\mu(M)}{r[r+\delta+\xi+\mu(M)]}$, $\Phi_2 \equiv \frac{\mu(M)R(M)+c(r+\delta+\xi)}{r[r+\delta+\xi+\mu(M)]}$ and $\kappa_C = \frac{\mu(M)}{(\delta+\xi+\mu(M))}$ is the fraction of time a position is filled when the firm is in the high state. In the low state, the firm is idle and receives zero profits. Again, the term under brackets corresponds to the present discounted value of a position, as in eq. (C.3).

We obtain that

$$p_h = \frac{\eta}{\eta-1}\frac{\Phi_2}{\phi\Phi_1}$$

$$\bar{L}_C = \left(\frac{1}{\varepsilon_h}\frac{\eta}{\eta-1}\frac{\Phi_2}{\Phi_1}\right)^{-\eta}\frac{\bar{Q}}{\kappa_C}\phi^{\eta-1}$$

and the expected profit

$$\Pi_C(\phi, \varepsilon, M) = \frac{1}{2}\varepsilon_h^{\eta}\frac{\Phi_2}{\eta-1}\left(\frac{\eta}{\eta-1}\frac{\Phi_2}{\Phi_1}\right)^{-\eta}\frac{\bar{Q}}{\kappa_C}\phi^{\eta-1}. \tag{C.22}$$

In this model, the impact of demand shocks on firms' outcomes depends on their strategy. Under Business-as-usual, the firm's employment is constant and prices are adjusted to shocks. Instead, the churning strategy allows firms to adjust to demand shocks through quantities, and thus prices are independent of demand shocks.[46]

[45] It should be noted here that handling non-zero demand in the low state is straightforward conceptually. In such a scenario, the firm churns over $\bar{L}_C$ and hires $\bar{L}_C^P$ permanent workers to ensure sufficient production to serve demand in the low state. However, given the maximization problem of the firm is then not separable in $\bar{L}_C$ and $\bar{L}_C^P$, it is impossible to get a full characterization for the optimal measures of positions, prices nor the value function. This is why we set $\varepsilon_l = 0$ to obtain an explicit solution to the problem.

[46] Note that this is true in the extreme case in which production is zero in the low state. But if churning firms had to combine permanent and churning positions, their price in the high state would be more complicated to determine as the high state would combine permanent and adjustable positions.

The firm compares the expected gains from pursuing the Business-as-usual strategy and Churning. The latter is preferred if the following holds:

$$\Gamma_2 \left(\frac{\Gamma_1}{\Gamma_2}\right)^{\eta} \kappa_C < \frac{1}{2}\varepsilon_h^{\eta}\Phi_2 \left(\frac{\Phi_1}{\Phi_2}\right)^{\eta} \kappa_B \tag{C.23}$$

The condition depends on structural parameters and location through $R(M)$ and $\mu(M)$ but not on firm productivity ϕ. A sufficient condition is that $R(M) > c$ and $\mu(M) > \xi$, exactly the conditions needed for churning in the base model (see Assumption 1). Moreover, as $\xi \to 0$ firms always prefer to churn. It is only if demand levels change frequently, that firms may prefer to keep workers instead of constantly readjusting the labor force and saving on operating and hiring costs in low states of demand at the expense of waiting to hire when its demand turns high. In the calibration used in Section 3, condition (C.23) is met.

In what follows, we will thus discern between two types of firms: non-volatile ones (that follow the Business-as-usual strategy) and volatile that churn.

Equilibrium distribution of volatile and non-volatile firms — After firms learn their productivity and demand volatility, they decide whether to pay a fixed cost f_p to produce. This defines the cutoff productivity values for firms that break even, conditional on their volatility denoted $\phi^*(0)$ and $\phi^*(\varepsilon)$ respectively:

$$\Pi_B\left(\phi^*(0), 0, M\right) = \Pi_C\left(\phi^*(\varepsilon), \varepsilon, M\right) = f_p. \tag{C.24}$$

This implies a linear relationship between the productivity cutoffs for volatile and non-volatile firms $\phi^*(\varepsilon) = \Omega\phi^*(0)$ where $\Omega^{\eta-1} \equiv 2\varepsilon_h^{-\eta}\frac{\Gamma_2}{\Phi_2}\left(\frac{\Gamma_2}{\Phi_2}\frac{\Phi_1}{\Gamma_1}\right)^{-\eta}\frac{\kappa_C}{\kappa_B}$. If eq. (C.23) holds, $\Omega < 1$ and $\phi^*(\varepsilon) < \phi^*(0)$ i.e. the productivity cut-off is lower for volatile than non-volatile firms, as in the base model of Section 3.

For a firm considering paying entry cost f_E, the expected profit depends on

$$\begin{bmatrix} \chi\left[\left(1 - G\left(\phi^*(0)\right)\right)\int_{\phi^*(0)}^{\infty}\left(\Pi_B\left(\phi, 0, M\right) - f_p\right)\frac{g(\phi)}{(1-G(\phi^*(0)))}d\phi\right] \\ +\left(1-\chi\right)\left[\left(1 - G\left(\phi^*(\varepsilon)\right)\right)\int_{\phi^*(\varepsilon)}^{\infty}\left(\Pi_C\left(\phi, \varepsilon, M\right) - f_p\right)\frac{g(\phi)}{(1-G(\phi^*(\varepsilon)))}d\phi\right] \end{bmatrix} = f_E$$

Letting $\tilde{\phi}(\cdot) := \left(\frac{1}{1-G(\phi^*(\cdot))}\int\limits_{\phi^*(\cdot)}^{\infty}\phi^{\eta-1}g\left(\phi\right)d\phi\right)^{\frac{1}{\eta-1}}$, this simplifies to:

$$\left[\chi\left(1 - G\left(\phi^*(0)\right)\right)\left(\left(\frac{\tilde{\phi}(0)}{\phi^*(0)}\right)^{\eta-1} - 1\right) + \left(1-\chi\right)\left(1 - G\left(\phi^*(\varepsilon)\right)\right)\left(\left(\frac{\tilde{\phi}(\varepsilon)}{\phi^*(\varepsilon)}\right)^{\eta-1} - 1\right)\right] = \frac{f_E}{f_p} \tag{C.25}$$

Since $\phi^*(\varepsilon) = \Omega\phi^*(0)$ we can obtain the solution for $\phi^*(0)$ from eq. (C.25).

With the Pareto productivity distribution, condition (C.25) becomes

$$\chi\left(\phi^*(0)\right)^{-\nu} + (1-\chi)\left(\phi^*(\varepsilon)\right)^{-\nu} = \frac{f_E}{f_p}\frac{(\nu-\eta+1)}{(\eta-1)}\left(\varphi_{\min}\right)^{-\nu}.$$

The measures of non-volatile firms N_B and volatile firms N_C that respectively use Business-as-usual and Churning strategies are given by $N_B = \chi[1-G(\phi^*(0))]N$ and $N_C = (1-\chi)[1-G(\phi^*(\varepsilon))]N$ where N is the measure of entering firms. The share of non-volatile to volatile firms is determined by the productivity cutoffs $\phi^*(0)$ and $\phi^*(\varepsilon)$. With the Pareto productivity distribution, this is given by

$$\frac{N_B}{N_C} = \frac{\chi}{(1-\chi)}\left(\frac{\phi^*(\varepsilon)}{\phi^*(0)}\right)^{\nu} = \frac{\chi}{(1-\chi)}(\Omega)^{\nu}$$

The share of firms of each type comoves with the relative productivity thresholds of non-volatile and volatile firms. We can show that for η high enough, a faster filling rate $\mu(M)$ and higher operating costs $R(M)$ ceteris paribus (holding the labor market tightness constant) increase the share of volatile churning firms as those benefit more from faster hiring and savings on operating in low demand periods. If we further assume that f_p is increasing with $R(M)$, we can show that for ν high enough, $\frac{\partial(\phi^*(\varepsilon))}{\partial R(M)} > 0$ or selection on productivity increases with city size. Given that $\frac{\partial \Omega}{\partial R(M)} < 0$, the productivity-density gradient is thus flatter for volatile firms.