Churning in Cities: The Volatility Advantages of Large Labor Markets*

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Within-firm employment volatility is higher in denser cities. We offer an explanation for this novel finding based on firms' entry and employment turnover decisions. Firms that face volatile demand for their products find it more profitable to adjust their workforce when they locate in local labor markets that allow for faster hiring even if it comes at the cost of more expensive operational costs. We estimate a firm location choice model on French data and show that more volatile firms are more likely to settle in denser commuting zones, conditional on their productivity. This mechanism reduces the productivity-density gradient among more volatile firms.

JEL-Classification: R12, R32, J63

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1 — Introduction

The productivity-density nexus is a central tenet of economic geography and urban economics (Combes et al., 2012; Gaubert, 2018). The key idea in this literature is that agglomeration economies benefit particularly high-productivity firms. In this paper, we focus on one mechanism of agglomeration economies, namely matching economies, i.e. the idea that larger cities make it faster to find suitable worker-firm matches. Since high-productivity firms are also relatively more profitable in larger markets, they have more to lose from waiting to fill a vacancy. We examine how matching economies interact with a salient firm characteristic – its structural demand volatility. By requiring firms to adjust their size positively or negatively in response to corresponding demand shocks, demand volatility increases the likelihood that firms find themselves in the position of needing to fill a vacancy, thus reinforcing the above mechanism. We argue that this dimension helps us understand firm sorting patterns across space and the functioning of local labor markets.

We start by documenting new facts about firms' productivity, firms' volatility, and local (working-age) population density. We use rich French administrative data at the worker and firm level over the 2010-2019 period, identifying (large) cities with (dense) commuting zones. Our first central finding is that within-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 meaningful and is barely reduced if we also control for firm productivity. The second important empirical result is that we find a flatter productivity-density gradient among firms that have high employment volatility. The elasticity of firms' average productivity to density is halved when moving from the first to the last decile of the volatility distribution.

We provide a simple search model inspired from Mortensen and Pissarides (1994) to rationalize these facts. Firms in the model differ in their productivity and the volatility of their sales. The economy alternates between good and bad states and the variance of sales induced by these cycles is heterogeneous across firms. Firms can mitigate the impact of volatility by adopting three different labor employment strategies. The first one aims to preserve the level of employment even in bad states and is chosen by the most productive firms. In the second one, the firm freezes hiring in bad states. Freezing hiring avoids facing operational costs in bad states, at the cost of entering good states with vacant positions. In the third one, firms "churn": they use an employee turnover strategy, firing workers when hit by bad shocks and hiring only when their demand is high. The latter strategy is preferred by the most volatile firms (fixing productivity) and by the least productive firms (fixing volatility). In comparison with a model that does not incorporate volatility and its impact on firms' labor employment strategies, our model thus displays a weaker selection on productivity.

The model then allows us to analyze where firms will 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 match faster with workers.[1] In particular, large cities enable firms to find workers faster when they are needed — when firms enjoy a positive productivity shock. Intuitively, locating in a large city provides an "insurance" against volatility, as larger cities offer lower adjustment costs for firms. This mechanism is particularly beneficial to high-productivity firms, which have the most to gain from being able to hire more quickly. Therefore, the model predicts that (i) firms sort positively on productivity and on volatility; (ii) those two dimensions reinforce each other; and (iii) the resulting gradient of firm productivity to city density decreases with firm volatility.

Motivated by our theoretical results, we estimate a firm location choice model

1. We remain agnostic on the source of the advantage in the matching technology of large cities. It may come from thicker labor markets (Gan and Zhang, 2006), increasing returns to scale in the matching technology (Petrongolo and Pissarides, 2006), more precise assortative matching (Dauth et al., 2022), or a greater variety of workers available to firms, allowing for higher match quality (Papageorgiou, 2022).

and compare the impact on location choices of heterogeneity in both productivity and volatility. We propose a novel strategy to measure the exogenous component of a firm's employment volatility. The measure is akin to a shift-share and combines information on the firm's portfolio of products with the time-serie of international demand at the product level. With this data, we measure the expected volatility of demand resulting from a firm's decision to produce a certain portfolio of products, which we assume exogenous to its location choice. We then estimate how productivity and demand volatility correlate with firms' location choices in the entry stage. Our estimates show that more volatile firms are more likely to settle in denser commuting zones. In addition, firm demand volatility is almost as predictive of firm location choice as firm productivity. Finally, in line with the theory, our estimates show that firm demand volatility and firm productivity are complements in firm location choice.

Relationship to the literature — Many studies provide theory and evidence that more productive firms sort into larger cities such as Combes (2000) and Gaubert (2018). Our work presents a new mechanism for agglomeration economies, based on the combination of firm productivity and volatility: matching economies emerge endogenously from firms' hiring and firing decisions when they face more expensive operational costs. This mechanism may also help understand why relatively unproductive firms can survive in denser areas (Combes et al., 2012), in addition to the mechanisms that have already been put forward in the literature.[2]

Similarly, current leading models of spatial labor markets (Bilal, 2021; 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 unem-

2. Another mechanism, also based on firm entry, is that higher entry costs in larger cities shield unproductive firms against the competition of other firms if entry is decided prior to the realization of productivity (Melitz, 2003; Schmutz and Sidibé, 2021). On the worker side, it has been argued that low-skilled workers can be found in large cities because of extreme-skill complementarity (Eeckhout et al., 2014).

ployment rates. However, these studies do not relate these observations directly to city size. In the data, large cities are characterized by both a higher share of high-productivity firms, and by higher unemployment rates.[3] One reason for this could be that the mobility of unemployed workers acts as a balancing force in spatial equilibrium (Gaigne and Sanch-Maritan, 2019). Yet, churning strategies used by firms provide an alternative explanation: if firms in large labor markets have higher demand volatility and consequently higher employment volatility, there may be more aggregate labor turnover and also more unemployment. This mechanism mitigates the negative effect on unemployment that may be caused by the agglomeration of more productive firms in larger cities.

More generally, this work complements the literature on the spatial dimension of matching in cities, which, until now, has largely focused on the worker side (Gan and Zhang, 2006; Bleakley and Lin, 2012; Papageorgiou, 2022; Dauth et al., 2022) with some incomplete evidence on firms (Glaeser et al., 1992; Henderson et al., 1995; Combes, 2000; Duranton, 2007; Findeisen and Südekum, 2008). Contrary to recent papers 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 in the labor market and we focus on hiring speed as the sole determinant of agglomeration economies. Moreover, in contrast to existing literature on the firm side, we do not address structural characteristics of the economy, such as sectoral composition. We focus on the impact of firm volatility, which is measured conditionally on the sector in which the firm operates. To that end, we appeal to the churning concept, whereby firms adjust their workforce to cope with individual fluctuations in their activity. We enrich the descriptive literature on labor market churning (Burgess et al., 2000; Nekoei and Weber, 2020; Weingarden, 2020) by introducing a spatial component, and a new, firm-specific shifter of employment volatility.

The remainder of the paper is organized as follows: in Section 2, we provide

3. See Appendix Figure C.1 for the case of the French commuting zones.

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 lay out a simple model of firm entry 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

The empirical analysis exploits matched employer-employee data for France over the period from 2010 to 2019 (INSEE DADS Postes). This data allows us to characterize the level and volatility of a firm's labor demand, at the monthly level. For each employer-employee relationship, we know the type of contract, the number of hours and remuneration. On the employer's side, we know the location of each establishment, as well as the sector of activity. Finally, the data can be matched with two additional yearly firm-level datasets, namely balance-sheet data used to estimate productivity (INSEE-FARE) and a production survey (INSEE-EAP) which provides additional information on the firm's portfolio of products.[4]

The analysis focuses on firms belonging to the manufacturing or business service sectors.[5] We use information on the firm's address to assign each plant to a commuting zone. Our sample includes plants in mainland France, which is composed of 280 distinct commuting zones. Since the focus is on how firms locate over space, we

4. The INSEE-EAP survey is exhaustive for firms in the manufacturing sector above a 20-employee size threshold. Merging the employer-employee linked data with the this survey induces severe censoring. The stylized facts discussed in this section exploit the full sample and we restrict the analysis to firms in the EAP survey when we need an exogenous measure of volatility, in section 4.

5. We exclude the public sector, agriculture, forestry and fishing, finance and insurance, the production and distribution of energy and waste, artistic activities, overseas activities, and the household service sector.

aggregate plant-level information at the level of a commuting zone, i.e. firms with multiple establishments in the same commuting zone are treated as a single plant.

We gather information on commuting zones from several sources. Each commuting zone is characterized by its population density, defined by the size of its working-age population divided by its area (in squared kilometers). Table 1 provides statistics about the distribution of commuting zones.

Table 1 — Population density and firms by commuting zone

	Density	Number of firms
Mean	150.75	569.22
Std dev	496.48	1937.41
25th percentile	39.74	164.5
50th percentile	68.69	260.5
75th percentile	122.32	482

Notes: Density corresponds to working age population divided by the commuting zone's area in squared kilometers. Density corresponds to the 2015 value, while the number of firms is calculated for the January 2015 cross section of the dataset.

Firms differ by their size, which the literature typically explains by some randomness in the firm's productivity, but also by the volatility of their labor demand, which our model will assume is the consequence of demand volatility. We estimate firm total factor productivity following Combes et al. (2012) – see details in Appendix A.1. We further 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:

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

where $\gamma_{f,t}$ is the year-on-year monthly growth rate of labor demand[6] and $\bar{\gamma}_{f,t}$ is

6. Monthly growth rates of labor demand are winsorized at the 1st and 99th percentile.

the mean growth rate computed over the $(2\omega + 1)$-month period centered around date t. Our baseline measure uses 35-month rolling windows. The variable is constructed using either employment or number of hours, with the latter capturing both intensive and extensive adjustments in labor demand. Moreover, our measure of employment volatility captures second-moments in the time-series of labor demand at firm-level, thus treating symmetrically upward and downward adjustments.

Table 2 — Distribution of employment volatility and productivity

	Number of employees	Log Employment volatility	Log Productivity
Mean	13.03	-1.78	-1.53
Std dev	25.73	0.80	1.17
25th percentile	3	-2.31	-2.09
50th percentile	6	-1.78	-1.31
75th percentile	12.9	-1.25	-0.72
Number of firms	159,381		

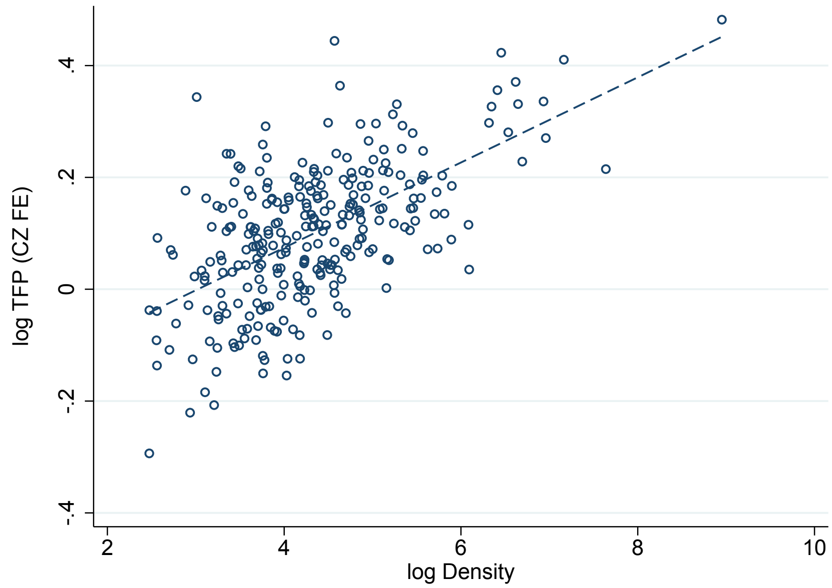
Notes: The size of plants and log employment volatility are calculated for the January 2015 cross section of the dataset. Log productivity is based on 2015 balance-sheet data.

Table 2 contains descriptive statistics on the baseline sample of firms. The motivating stylized facts rely on a cross-section of firms. We use the January 2015 cross-section but results are robust to choosing any different reference period. In January 2015, the sample is composed of 159,381 firms that we observe over at least 35 periods. As expected, firms display significant heterogeneity in size, employment volatility, and productivity.

2.2. Motivating stylized facts

The literature in economic geography has long discussed agglomeration patterns of firms over space. The proximity-density nexus, i.e. the tendency of high-productivity firms to agglomerate in dense cities, has been a central tenet of the literature, following Combes et al. (2012). We reproduce the evidence using our data in Figure 1.

Figure 1 — The productivity advantage of dense cities



Notes: The figure 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 is conditional on the following firm characteristics: sector, size bin, and age. The slope is equal to 0.0762 and is significant at the 1% level.

More precisely, we first run the following regression based on the cross-section of firms observed in January 2015:

$$tfp_{f(M)} = X_{f(M)} + FE_M + \varepsilon_{f(M)} \tag{2}$$

where $tfp_{f(M)}$ is the (log of the) firm's TFP, $X_{f(M)}$ is a set of controls and FE_M 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 sector of activity, its size bin and age.[7]

Figure 1 shows how conditional average productivity correlates with the popu-

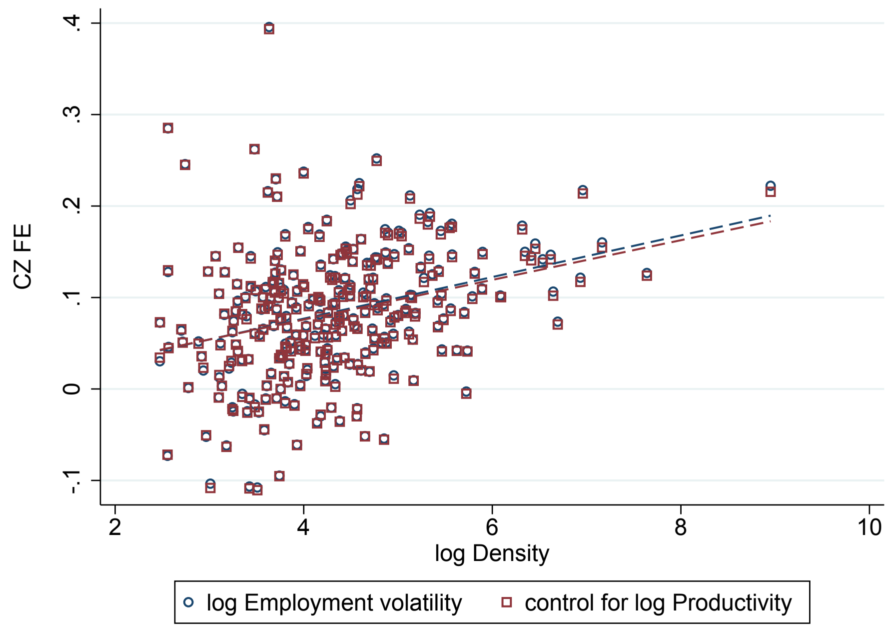
7. More precisely, we use 2-digit sector fixed effects and 6 size bins for plants, which identify plants below 2 employees, between 2 and 9 employees, between 10 and 49 employees, between 50 and 249 employees, between 250 and 4,999 employees, and above 5,000 employees.

lation 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 with higher meeting rates are most beneficial to high-productivity firms that are able to hire more quickly (Bilal, 2021). To the extent that pooling externalities are part of the story, we shall expect that the benefit is also larger for more structurally 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.

We provide preliminary evidence for a role of employment volatility in Figure 2. As in Figure 1, we first recover an estimate of firms' average employment volatility at the commuting zone level. We run a regression similar to equation (2), using the log of employment volatility. 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 denser commuting zones. Importantly, the set of controls for the red scatter now includes the firm's productivity, which implies that a positive correlation exists beyond and above the productivity-density nexus that the literature before us has documented.

A natural concern here is however that productivity and employment volatility are correlated which implies that the relationship in Figure 2 may be the consequence of the productivity-density nexus illustrated in Figure 1. In the model and the empirical analysis, we will systematically take this possibility into account. Before entering into the details of the relationship, Figure 3 provides an additional motivating stylized fact that directly tackles this joint correlation between employment

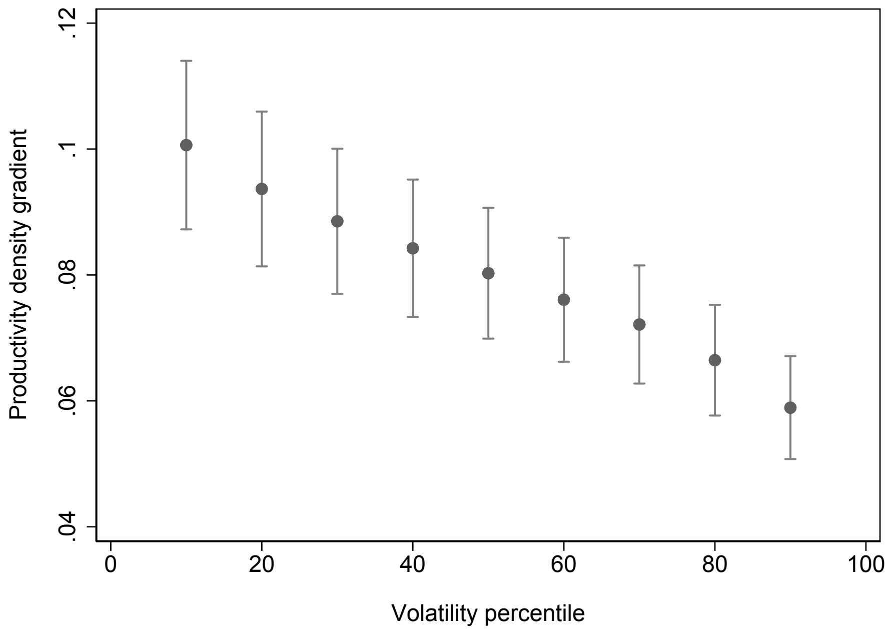
Figure 2 — The volatility advantage of dense cities



Notes: The figure shows the correlation between the mean volatility of firms and the density of the commuting zone where they locate. Volatility is measured by the standard deviation of the firm's labor demand. Mean volatility is based on the January 2015 cross section of firms and is conditional on the following firm characteristics: sector, size bin, firm age (the blue scatter) and also log productivity (the red scatter). The slope is 0.0227 when we do not control for log productivity (the R2 is 0.0873) and 0.0217 when we control for log productivity (the R2 is 0.0943). Both slopes are significantly different from 0 at 1%.

volatility and productivity. Instead of recovering the correlation between firms' attributes and the commuting zone of choice in two stages, we now directly introduce commuting zone density in equation (2). The downside is that we can no longer control for unobserved heterogeneity between commuting zones using fixed effects. However, we can now interact density with a measure of the firm's employment volatility to estimate how the productivity-density correlation varies depending on the firm's volatility. The coefficient on the interaction is negative and strongly significant, which implies that the tendency of high-productivity firms to agglomerate in dense cities is less pronounced within the set of more volatile firms. Quantitatively, the cross-correlation is non-negligible: The elasticity of firms' average productivity

Figure 3 — The productivity-density nexus, along the distribution of volatility



Notes: The figure shows the conditional correlation between log productivity of firms and the density of the commuting zone where they locate, along the distribution of firms' log employment volatility. Productivity is conditional on the following firm characteristics: sector, size bin, firm age and employment volatility. The estimated equation includes the log density of the commuting zone where the firm is located, and its interaction with the firm's volatility. Volatility is measured by the standard deviation of the firm's labor demand. Data is based on the January 2015 cross section of firms.

to density is halved when moving from the first to the last decile of the volatility distribution.

All in all, the evidence in this section confirms that denser cities attract a pool of firms that are systematically 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 employment volatility. The model's main prediction reads as follows: if firms sort across space based on their 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 employment volatility.

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 productivity shocks and hiring frictions. The economy operates at a steady state and time is continuous. We focus on 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.

Firms are heterogeneous in terms of their mean productivity $p \in [\underline{p}, \overline{p}] \subset \mathbb{R}^+$ and their demand volatility $\varepsilon \in [0, 1]$, both known ex ante (before entry) and independent from each other. Sales fluctuate in any period between $p(1 + \varepsilon)$ in high state (h) and $p(1 - \varepsilon)$ in low state (l) at exogenous rate σ. While both p and ε are heterogeneous among firms, σ is a structural parameter of the economy.

Upon entry, firms choose a location or city defined by its density $M > 0$ and become immobile. City choice determines firms' operational costs $R(M) \geq 0$ and job-filling rate $\mu(M) \geq 0$. Those two local factors are not impacted by firms' decisions. $R(M)$ is a local index that combines all costs associated with maintaining an active position.[8] 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. We assume that $R(M)$ and $\mu(M)$ are both increasing in M.[9]

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 operational 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.

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

$$
\begin{aligned}
rV_s^h(p,\varepsilon,M) &= -c + \mu(M)[A_s^h(p,\varepsilon,M) - V_s^h(p,\varepsilon,M)] \\
&+ \sigma[W_s(p,\varepsilon,M) - V_s^h(p,\varepsilon,M)]
\end{aligned}
\tag{3}
$$

$$
rV_s^l(p,\varepsilon,M) = -c + \mu(M)[A_s^l(p,\varepsilon,M) - V_s^l(p,\varepsilon,M)] \tag{4}
$$

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

9. While $R'(M) > 0$ is easily justified by a congestion argument, the sign of $\mu'(M)$ is more contentious because it depends directly on the equilibrium number of firms in each location.

$$
\begin{aligned}
& + \quad \sigma[V_s^h(p,\varepsilon,M) - V_s^l(p,\varepsilon,M)] \\
rA_s^h(p,\varepsilon,M) &= p(1+\varepsilon) - R(M) + \delta[V_s^h(p,\varepsilon,M) - A_s^h(p,\varepsilon,M)] \quad (5) \\
& + \quad \sigma[C_s(p,\varepsilon,M) - A_s^h(p,\varepsilon,M)] \\
rA_s^l(p,\varepsilon,M) &= p(1-\varepsilon) - R(M) + \delta[W_s(p,\varepsilon,M) - A_s^l(p,\varepsilon,M)] \quad (6) \\
& + \quad \sigma[A_s^h(p,\varepsilon,M) - A_s^l(p,\varepsilon,M)] \\
rI_s(p,\varepsilon,M) &= \sigma[V_s^h(p,\varepsilon,M) - I_s(p,\varepsilon,M)] \quad (7)
\end{aligned}
$$

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 ($W_s(p,\varepsilon,M)$) or being active in the low state ($C_s(p,\varepsilon,M)$), as summarized in Table 3:

Table 3 — Strategies and values of low state

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

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 $\mathbb{E}_s(p,\varepsilon,M) = 0.5 \times [V_s^h(p,\varepsilon,M) + W_s(p,\varepsilon,M)]$. Conditional on location, the *dominant strategy* s^* is thus the one that maximizes expected profit: $s^*(p,\varepsilon,M) = \arg\max_s [\mathbb{E}_s(p,\varepsilon,M)]$.

For simplicity, we normalize entry costs to zero. Note that even dominant 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 $M^*(p,\varepsilon)$ between firms' characteristics and location:

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

Productivity p and demand volatility ε, together with strategy s and location M determine volatility of employment σ_f.

3.2. Resolution

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. Expressions, proofs and further illustrations are provided in Appendix B.

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* that determine whether a given strategy is *feasible*, and two *switching cutoffs* that determine which strategy is dominant.

Strategy s is feasible for a type-(p,ε) firm if p is greater than the selection cutoff $\underline{p}_s(\varepsilon,M)$. Under strategy B, the selection cutoff $\underline{p}_B(\varepsilon,M)$ does not depend on ε and may therefore be denoted $\underline{p}_B(M)$. As is usual in this type of model, productivity must cover both operational costs and the vacancy cost at entry and following any exogenous separation. Under strategy W, the selection cutoff $\underline{p}_W(\varepsilon,M)$ 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 $\underline{p}_C(\varepsilon, M)$ is even more sensitive to ε than under strategy W: $\partial\underline{p}_C(\varepsilon, M)/\partial\varepsilon < \partial\underline{p}_W(\varepsilon, M)/\partial\varepsilon$. However, the selection cutoff also entails a fixed cost $c\sigma/\mu(M)$, which corresponds to the supplement of 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.[10]

We then turn to the conditions that determine when firms adopt a churning strategy over alternative strategies. In what follows, an *adopted strategy* is both dominant and feasible. We denote by $\underline{p}_{BW}(\varepsilon, M)$ and $\underline{p}_{WC}(\varepsilon, M)$, with $\underline{p}_{BW}(\varepsilon, M) > \underline{p}_{WC}(\varepsilon, M)$, the corresponding cutoffs. Both cutoffs, as well as the difference between the two, are convex increasing functions of ε. Regarding the B strategy, we can note that $\forall\varepsilon, \underline{p}_{BW}(\varepsilon, M) > \underline{p}_B(M)$. Therefore, if strategy B is dominant, it is also feasible, and therefore, adopted. Conversely, strategies W or C may be dominant, yet unfeasible, if $\underline{p}_{WC}(\varepsilon, M) < \underline{p}_W(\varepsilon, M)$ or $\underline{p}_{WC}(\varepsilon, M) < \underline{p}_C(\varepsilon, M)$. We use an arbitrary parametrization of the model to represent the selection and switching cutoffs as a function of ε in Appendix Figure B.1.

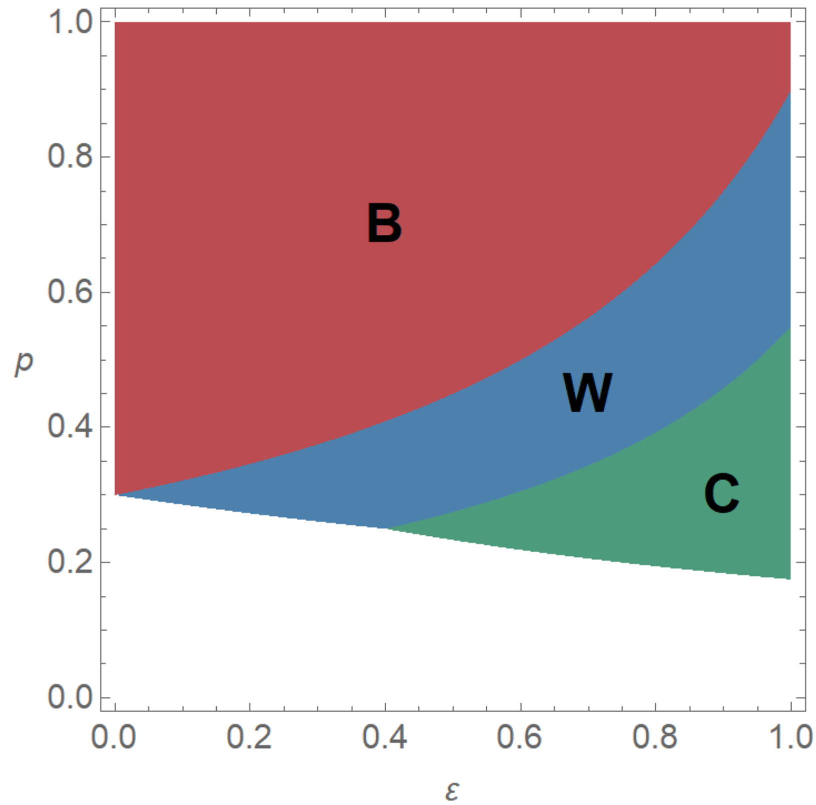
Equipped with these definitions, we can fully characterize the distribution of adopted strategies as a function of p and ε. They are represented in Figure 4 in the form of the three regions labeled B, W, and C, for an arbitrary calibration of the model.[11] The figure highlights our first two key results that hold for a fixed city, as summarized in Proposition 1:

Proposition 1. STRATEGY CHOICE — In a given city,

10. This cutoff is given by $\tilde{\varepsilon}(M) = \frac{c(r+\delta+2\sigma)}{c(r+\delta)+2\mu(M)R(M)}$.

11. Note that one strategy may never be adopted, depending on the parameters. In particular, W disappears when $c \to 0$. Similarly, C would disappear if we introduced sufficiently high firing costs. Firing costs χ could be introduced in a more general model featuring $C_s(p, \varepsilon, M) - \chi$ instead of $C_s(p, \varepsilon, M)$ in Equation 7. See Appendix Figure B.2 for an illustration.

Figure 4 — Strategy choice under fixed city size



Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = 0.02$, $R(M) = 0.2$, $\overline{p} = 1$. The figure represents the set of (ε, p) combinations associated with each adopted strategy. The blank section corresponds to combinations that are not feasible, regardless of the strategy.

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

1.2 Very volatile firms may churn even if they are quite productive.

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.[12]

12. This assumption is verified under the condition $\tilde{\varepsilon}(M) < 1$, which is equivalent to $c/\mu(M) < R(M)/\sigma$. In words, this means that the expected vacancy cost is lower than the operational costs paid by the firm when it is operating in the low state. For simplicity, we will even assume a stronger

Assumption 2. Absent strategy switch, selection increases with density.[13]

Assumption 3. There exists an optimal level of density.[14]

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

Proposition 2. COMPARATIVE STATICS — If cities are heterogeneous in density,

2.1 Denser cities have a higher share of churning firms.

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

Results 2.1 and 2.2 can also be gauged by comparing dominant strategies in the (ε, p) plane for different levels of density, as we do in Appendix Figure B.3. In line with result 1.2, even the most 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.[15]

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 p and volatility ε.[16] While the combinations of (p, ε) associated with

condition, stating that $\forall M \geq 0, R(M) > c$ and $\mu(M) > \sigma$. Note that this means that both $R(M)$ and $\mu(M)$ feature a fixed positive component.

13. The most binding condition is for strategy C, where it is equivalent to: $R'(M) \geq (r + \delta + \sigma)\mu'(M)/\mu(M)^2$. For simplicity, and using Assumption 1, we will even assume a stronger condition on the relative elasticity of each function: $[R'(M)/R(M)]/[\mu'(M)/\mu(M)] > (r + \delta + \sigma)/\sigma$.

14. A sufficient condition for this assumption to be verified is that operational costs are convex in density, while the worker-finding rate is concave in density.

15. Note that result 2.1 is also consistent with our initial assumption that $\mu'(M) > 0$, provided the equilibrium number of firms per worker is non-decreasing with human density.

16. Appendix Figure B.4 illustrates this problem for low/high productivity/volatility firms.

strategy choice are only defined implicitly, the envelope theorem ensures that Proposition 1 is robust to firms' location choice.[17] In particular, more volatile firms are more likely to adopt the churning 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

We can use our framework 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* $p_s^*(\varepsilon, M) = \arg\max_p \mathbb{E}_s(p, \varepsilon, M)$ and $\varepsilon_s^*(p, M) = \arg\max_\varepsilon \mathbb{E}_s(p, \varepsilon, M)$.

The study of these sorting cutoffs allows us to write Proposition 3:[18]

Proposition 3. PREDICTIONS — If firms choose their location in order to maximize their expected profit upon entry,

3.1 More productive and more volatile firms sort into denser cities. Productivity and volatility are complements in city choice.

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

Prediction 3.2 echoes the aggregate sorting patterns described in Section 2. Figure 5 illustrates this prediction for an arbitrary calibration of the model. Panel A, consistent with Figure 2, displays the share of churning firms as an increasing function of density. In Panel B, we measure the productivity-density gradient along the

17. Appendix Figure B.5 illustrates this result. Note, however, that since the strategies are very different from one another, the sorting of firms involves discrete jumps in density when firms switch strategies, as shown in Appendix Figure B.6.

18. See Appendix Figure B.7 for an illustration.

distribution of firm volatility. Consistent with Figure 3, this gradient decreases with firm volatility. As for prediction 3.1, it will be tested in Section 4.

4 — Volatility and firm location: empirical evidence

4.1. Empirical strategy

In order to test Prediction 3.1, we use a location choice model estimated with a conditional logit estimator and data on new firm openings. While the theoretical model assumed a continuum of densities, we now consider a discrete set of locations $\mathcal{M} = \{M\}$. We recover information on the birth date and location at entry of the firms in our sample and we use this to estimate the determinants of location choices. 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 $\mathbb{E}^*(p_f, \varepsilon_f, M) = \mathbb{E}_{s^*(p_f,\varepsilon_f,M)}(p_f, \varepsilon_f, M)$ for brevity. Assuming that the expected intertemporal 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:

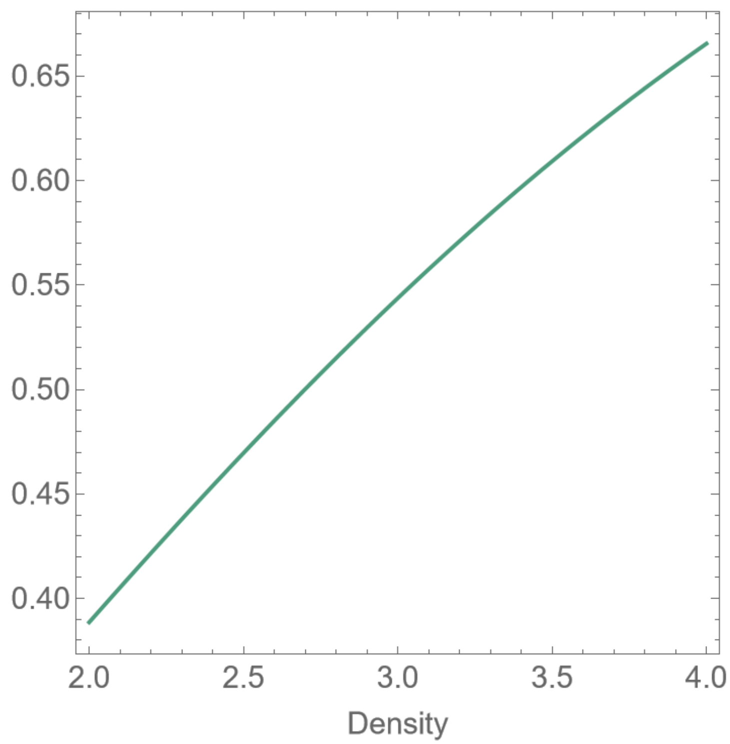
$$\begin{aligned} \mathbb{P}_{fM}|e_{fM} &= \mathbb{P}\left(\mathbb{E}^*(p_f, \varepsilon_f, M) + e_{fM} > \max_{M' \neq M} \{\mathbb{E}^*(p_f, \varepsilon_f, M') + e_{fM'}\}\right) \\ &= \frac{\exp\left[\mathbb{E}_{s^*(p_f,\varepsilon_f,M)}(p_f, \varepsilon_f, M)\right]}{\sum\limits_{M' \in \mathcal{M}}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

where the second line uses the assumption that e_{fM} is independently, identically distributed extreme value (Gumbel, type 1 extreme value).

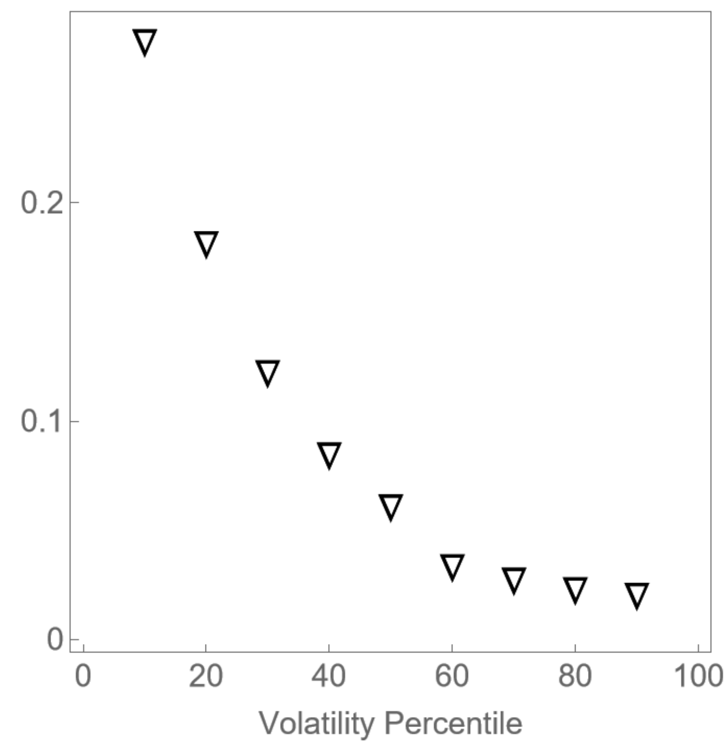
Our model predicts the choice between all commuting zones to be a function of the size of operational costs $R(M)$ and the job-filling rate $\mu(M)$ as well as their interaction with firms' productivity p_f and (structural) demand volatility ε_f. Following the theoretical model, the baseline logit model considers the role of commuting zone

Figure 5 — Volatility and the sorting of firms

A - Share of churning firms



B - Volatility and the productivity-density gradient



Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. We assume that p and ε are independent, ε is uniformly distributed over $[0, 1]$ and p follows a (truncated) Pareto distribution, so that $h(p, \varepsilon) = 4 \times 0.1^4 / \times p^5$. The optimum is found by a numerical search. **Panel A:** The share of churning firms is given by $C(M) = \frac{\int\int \mathbf{1}_{C=s^*(p,\varepsilon,M)} h(p,\varepsilon) dp d\varepsilon}{\int\int \sum_s \mathbf{1}_{s=s^*(p,\varepsilon,M)} h(p,\varepsilon) dp d\varepsilon}$. **Panel B:** For each decile d of the distribution of ε, let $d_\varepsilon = [d - 5\%, d + 5\%]$. The average productivity of firms in this decile of volatility is given by $p^*(M, d) = \frac{\int\int_{d_\varepsilon} \sum_s \mathbf{1}_{s=s^*(p,\varepsilon,M)} p_s^*(\varepsilon, M) h(p,\varepsilon) dp d\varepsilon}{\int\int_{d_\varepsilon} \sum_s \mathbf{1}_{s=s^*(p,\varepsilon,M)} h(p,\varepsilon) dp d\varepsilon}$. Then, $\nabla(d) = p^*(3, d) - p^*(2, d)$.

density, and its interaction with firms' characteristics, TFP and volatility. We also control for other commuting zone characteristics that are important for firm location decisions, namely two measures of the workforce skill (the share of managers, the share of college graduates) and a measure of localization economies.

Localization economies — Localization economies measure a firm's sectoral network based on Mayer et al. (2010). This sectoral network is calculated as the cumulated number of firms in the same industry located in each potential commuting zone in the year preceding the firm's creation. More precisely, localization economies are defined as:

$$SectoralNetwork^{s}_{i,t-1} = \sum_{u<t} \sum_{a} D^{s}_{ai,u} \tag{9}$$

where $D^{s}_{ai,u}$ is a dummy variable equal to one for all firms a of sector s located in commuting zone i and created in year u or before. The count of firms in each sector and commuting zone only includes firms with positive employment.

Demand volatility — Although the implementation of the model is in principle straightforward, there is one additional difficulty. In the context of our model, volatility of employment is endogenous to the firm's strategy choice, which itself depends on the joint impact of the firm's productivity and demand volatility. We tackle the problem by proposing a novel measure of a firm's demand volatility, which is less endogenous than volatility of employment used in Section 2. The proposed measure uses exogenous variations in export demand for products in the firm's portfolio. More specifically, we use the EAP survey to recover information on the structure of a firm's product portfolio in some base period:

$$w_{fp,0} = \sum_{p} \frac{Sales_{fp,0}}{\sum_{p' \in P_{f,0}} Sales_{fp',0}}$$

where $Sales_{fp,0}$ is the value of product-level sales and $P_{f,0}$ denotes the set of products in the firm's portfolio in base period 0.

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:

$$\gamma^D_{f,t} = \sum_{p' \in P_{f,0}} w_{fp',0} \gamma^D_{p',t}$$

where $\gamma^D_{p',t}$ is the year-on-year growth of the world demand[19] of product p' recovered from Eurostat trade data. We can finally compute a measure of expected demand volatility:

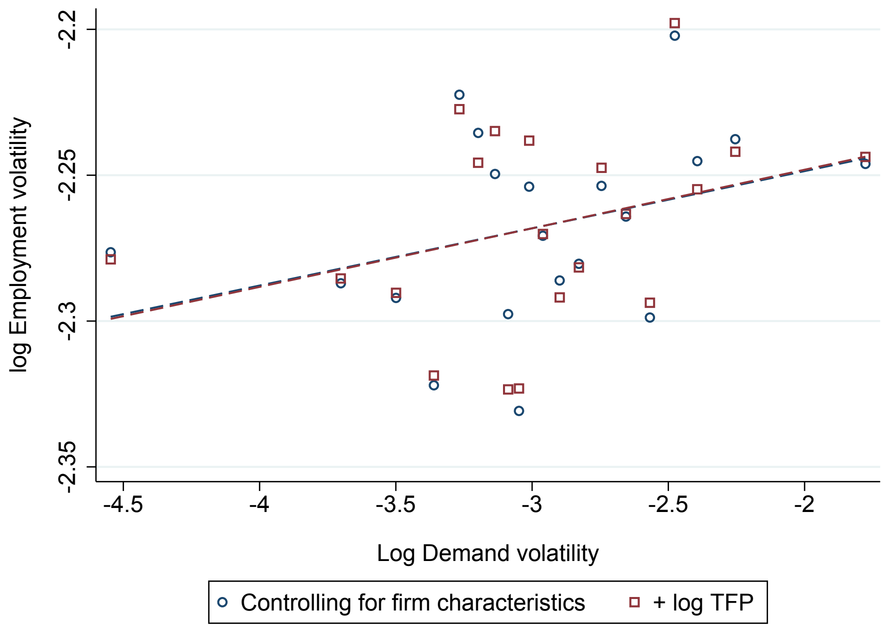
$$\varepsilon_{f,t} = \left[\frac{1}{2\omega + 1} \sum_{\tau=-\omega}^{\omega} (\gamma^D_{f,t+\tau} - \bar{\gamma}^D_{f,t})^2 \right]^{\frac{1}{2}} \tag{10}$$

In comparison with $\sigma_{f,t}$, 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. From this point of view, it is more exogenous to the firm location choice than the volatility of labor demand. However, strict exogeneity requires that the structure of the firm's portfolio is given, at the time of the location decision. To give credibility to the assumption, we use information on the firm's portfolio of products observed during the first year of activity.

Unfortunately, the use of the EAP survey forces us to focus on a sub-sample of the firms in our data, which is not necessarily representative of the whole population. Table A.1 in the Appendix compares the main characteristics of firms with and without information on demand volatility in the January 2015 cross section. The sample for which demand volatility is non-missing selects relatively larger and older firms, for which labor demand is less volatile than the average. However, differences in employment volatility disappear between the two samples when we control for observed firm characteristics. As shown in Figure 6, the correlation between em-

19. World demand refers to imports from all countries in the world excluding France.

Figure 6 — Employment volatility and demand volatility



Notes: The figure shows the correlation between firms' employment volatility and demand volatility, for 20 bins of demand volatility. Employment volatility is based on the January 2015 cross section of firms for which demand volatility may be computed and is conditional on the following firm characteristics: sector, size bin, firm age (circles) and productivity (squares).

ployment volatility and demand volatility is quite strong, even though they stem from completely different sources.

4.2. Results

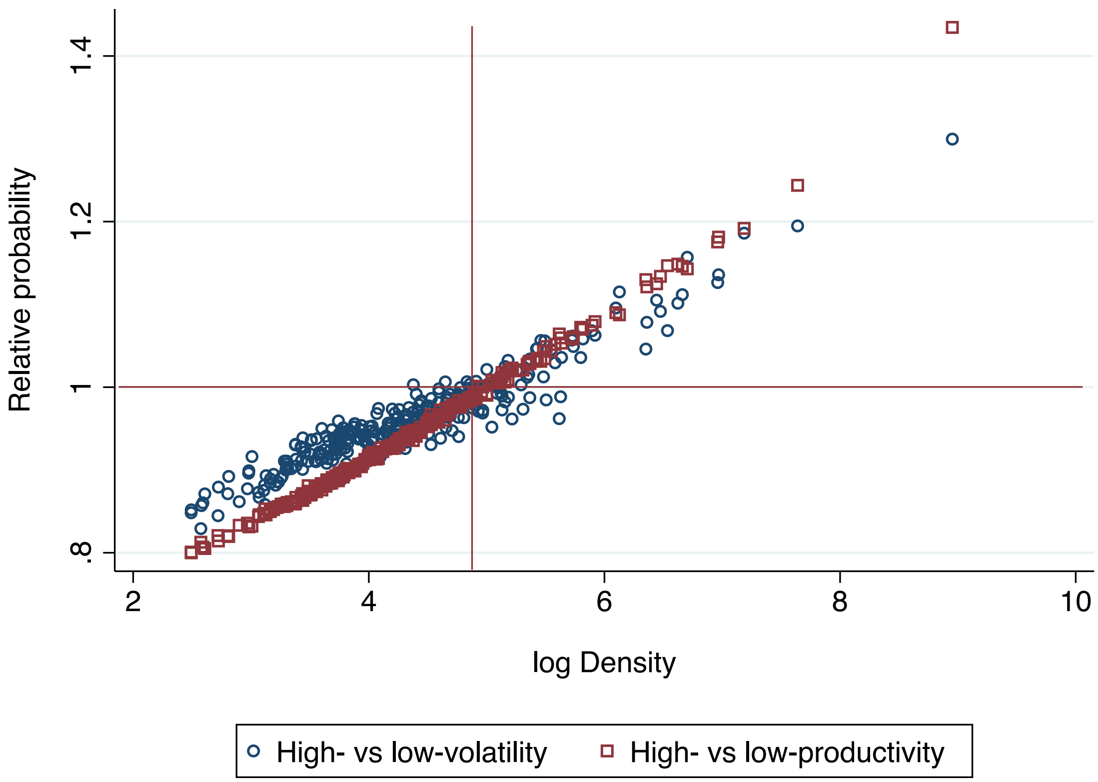
The final sample used in the estimation of the location choice model is described in Appendix Table A.2. Newly-created firms tend to be more productive than older firms, and they are located in somewhat less dense CZs. Conversely, their demand volatility is quite comparable to the demand volatility of other firms. Estimation results are summarized in Table 4. In column (1), the only explanatory variable is the (log of) density of the commuting zone, and we confirm the tendency of firms to agglomerate in denser commuting zones. 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 columns (4)-(6), we simultaneously consider the two interaction terms (column 4) and add additional commuting-zone-specific controls (column 5) as well as commuting-zone-specific fixed effects (column 6). Results point to a quantitatively similar impact of productivity and volatility on location patterns, which is stable across specifications. Namely, the elasticity of the odds of choosing a specific location to the density of this commuting zone increases from .29 to .38 when moving from the first to the ninth decile of the distribution of productivity. The effect is similar (from .31 to .38), when moving along the distribution of demand volatility.

Table 4 — Results of the location choice model: main effects

	CZ choice					
	(1)	(2)	(3)	(4)	(5)	(6)
log Density	0.552 (0.019)	0.551 (0.019)	0.551 (0.019)	0.550 (0.019)	0.338 (0.027)	-
log Density * Volatility	No	No	0.034 (0.018) [1.005]	0.036 (0.018) [1.005]	0.036 (0.017) [1.003]	0.034 (0.017)
log Density * Productivity	No	0.041 (0.021) [1.006]	No	0.043 (0.021) [1.006]	0.038 (0.019) [1.003]	0.040 (0.020)
CZ characteristics	No	No	No	No	Yes	No
Localization economies	No	No	No	No	Yes	Yes
CZ FE	No	No	No	No	No	Yes
Num. observations	468,440	468,440	468,440	468,440	468,440	468,440
Pseudo R2	0.038	0.038	0.038	0.039	0.045	0.087

Notes: Coefficient estimates from a conditional logit model with firm fixed effects. The sample is based on all firm entries from January 2010 to December 2019 (1,673 entries). Volatility and productivity are standardized. Standard errors in round parentheses. Odds ratios in squared brackets.

Figure 7 — Heterogeneity in location choices, along the distributions of productivity and 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 cut-offs are based on firms at the 25th and 75th percentile of each distribution. The probabilities are recovered from the estimation of the model in column (5) of Table 4.

The heterogeneity in the determinants of location choices along the distribution of firms is further illustrated in Figure 7, which compares the probabilities of locating in a particular commuting zone, for firms at the 75th percentile relative to the 25th percentile of the distribution of firms' productivity and demand volatility. The patterns recovered from heterogeneous productivity and volatility are very similar. 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 are significantly more likely to locate in denser cities. Whereas the agglomeration of productive firms in dense cities is a well-known fact of the literature in economic geography, our results suggest that agglomeration patterns are equally strong along the volatility dimension.

Finally, we turn to the second part of Prediction 3.1, whereby productivity and volatility are complements 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). According to our theory, low-productivity firms may be able to survive in denser cities if they are volatile enough to be able to churn: volatility and productivity are substitutes regarding the effect of selection. Yet, the optimal sorting of firms works differently: more volatile firms should gain more from being able to churn (in denser locations) when they are, on average, more productive, because of the multiplicative structure between p and ε in the model.

In Table 5, we test this prediction by estimating the impact of the triple interaction between CZ density, firm productivity, and firm demand volatility. To that end, we use the most restrictive specification in Table 4, with commuting zone fixed effects. In column (1), we reproduce the estimates of column (6) in Table 4. In column (2), we augment this specification with the triple interaction: the coefficients on the main effects remain very stable, and the interaction is positive and significant. In column (3), we isolate the effect of productivity for high- and low-volatility firms. The estimate is virtually zero for low-volatility firms, and it is 2.5 times higher than the average effect for high-volatility firms. In column (4), we reproduce the analysis by breaking down the impact of volatility between high- and low-productivity firms, and the same pattern is observed as for productivity. Finally, column (5) shows that these heterogeneous effects can still be observed when we simultaneously distinguish between the impact of volatility for high- versus low-productivity firms and the impact of productivity for high- versus low-volatility firms. However, this last column suggests that sorting based on volatility may still be observed for low-productivity firms, albeit to a lower extent.

Table 5 — Results of the location choice model: interaction effects

	CZ choice				
	(1)	(2)	(3)	(4)	(5)
log Density * Volatility	0.034	0.034	0.034		
	(0.017)	(0.017)	(0.017)		
log Density * Volatility * High Productivity				0.061	0.042
				(0.022)	(0.024)
log Density * Volatility * Low Productivity				0.0004	0.024
				(0.026)	(0.027)
log Density * Productivity	0.040	0.041		0.039	
	(0.020)	(0.019)		(0.020)	
log Density * Productivity * High Volatility			0.107		0.100
			(0.034)		(0.037)
log Density * Productivity * Low Volatility			0.006		0.009
			(0.024)		(0.025)
log Density * Volatility * Productivity		0.046			
		(0.018)			
Localization economies	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes
Num. observations	468,440	468,440	468,440	468,440	468,440
Pseudo R2	0.087	0.088	0.088	0.088	0.088

Notes: Coefficient estimates from a conditional logit model with firm fixed effects. The sample is based on all firm entries from January 2010 to December 2019 (1,673 entries). Volatility and productivity are standardized. "High (respectively, low) volatility/productivity" are dummy variables equal to 1 if these standardized values are positive (respectively, negative). Standard errors in round parentheses.

5 — Conclusion

In this paper, we show that firms with a more volatile activity benefit from locating in denser locations. Larger operating costs associated with density create an incentive for volatile firms to adopt a more flexible workforce management strategy. In turn, those firms, by frequently releasing workers, generate a positive externality on other firms, which benefit from better hiring prospects. 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. However, our partial-equilibrium analysis does not allow for a welfare quantification of this mechanism. For example, workers should be compensated for working in more volatile firms. Similarly, from a theoretical perspective, the implications of this mechanism in terms of the extensive margin of firm entry – and therefore, the spatial distribution of firm density – are still unknown. We leave these extensions for further research.

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A — Data construction

A.1. Total Factor Productivity

We follow Combes et al. (2012) to calculate productivity. For each firm f and year y, productivity is calculated as:

$$ln(V_{fy}) = \beta_{0y} + \beta_1 ln(k_{fy}) + \beta_2 ln(l_{fy}) + \sum_{s=1}^{3} \sigma_s l_{sfy} + \phi_{fy} \quad (11)$$

where V_{fy} is value added, k_{fy} is capital, l_{fy} is labor (n. paid hours in y). As in Combes et al. (2012), we distinguish between skill levels: high, intermediate and low. Thus, l_{sfy} is the share of firm's workers with skill level s.

We estimate the equation separately for each 2-digit sector using OLS and obtain TFP as the residual:

$$\hat{\phi}_{ft} = ln(V_{ft}) - \hat{\beta}_{0t} - \hat{\beta}_1 ln(k_{ft}) - \hat{\beta}_2 ln(l_{ft}) - \sum_{s=1}^{3} \hat{\sigma}_s l_{sft} \quad (12)$$

In robustness checks, productivity is calculated using the Levinshon-Petrin estimation technique.[20] We also apply the Ackerberg et al. (2015) correction. Results are robust to different productivity measures.

A.2. Sample selection

In Table A.1, we compare two groups of firms in the January 2015 sample. The group with information on demand volatility has lower employment volatility, but the difference is mostly driven by other firm characteristics. In Table A.2, we compare the sample used in the location choice model and the subsample from the January 2015 cross-section with information on demand volatility. Both samples are comparable regarding demand volatility, less so regarding location and productivity.

20. We use the Stata *prodest* command which exploits the control function approach.

Table A.1 — Firms with and without demand volatility (January 2015)

	Not Missing	Missing	T-test equality of means
Size	26.50	12.18	38.17
	(35.89)	(24.71)	[0.00]
Age (years)	23.37	16.18	47.46
	(14.40)	(12.03)	[0.00]
log CZ Density	5.21	5.84	-39.13
	(1.51)	(1.83)	[0.00]
log Productivity	-1.64	-1.52	-9.30
	(1.19)	(1.17)	[0.00]
log Employment volatility	-2.27	-1.75	-59.11
	(0.82)	(0.79)	[0.00]
residualized log Employment volatility	-1.81	-1.78	-4.60
	(0.63)	(0.65)	[0.00]
N observations	9,425	149,956	

Notes: Means and standard deviations in round brackets, p-values of T-tests in square brackets. Residualized log Employment volatility is the residual from regressing employment volatility on CZ, sector, firm size, and age FEs, as well as log productivity.

Table A.2 — Firms in location choice sample and firms in January 2015 cross section

	In LCM sample	January 2015 cross-section	T-test equality of means
log CZ Density	5.00	5.21	5.57
	(1.51)	(1.51)	[0.00]
log Productivity	-1.41	-1.64	-6.31
	(1.06)	(1.19)	[0.00]
log Demand volatility	-2.92	-2.97	-2.73
	(0.79)	(0.74)	[0.01]
N observations	1,673	9,099	

Notes: Out of sample subsample is taken from the January 2015 cross section with non-missing log employment volatility, log productivity, log demand volatility, sector, firm age, size. For in-sample data we use the same data as in location choice model.Means and standard deviations in round brackets, p-values of T-tests in square brackets.

B — Theory

B.1. Definitions

Expected profits — Expected profits are given by:

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

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

$$r\mathbb{E}_C(p,\varepsilon,M = \frac{\mu(M)[p(1+\varepsilon)-R(M)]-c(r+\delta+\sigma)}{r+\delta+\sigma+\mu(M)} \tag{B.3}$$

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

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

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

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

$$\underline{p}_B(\varepsilon,M) = \underline{p}_B(M) = R(M)+\frac{c(r+\delta)}{\mu(M)} \tag{B.4}$$

$$\underline{p}_W(\varepsilon,M) = \left(\frac{r+\delta+2\sigma}{(1+\varepsilon)(r+\delta)+2\sigma}\right)\underline{p}_B(M) \tag{B.5}$$

$$\underline{p}_C(\varepsilon,M) = \frac{1}{1+\varepsilon}\left(\underline{p}_B(M)+\frac{c\sigma}{\mu(M)}\right) \tag{B.6}$$

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

$$\underline{p}_{BW}(\varepsilon,M) = \left(\frac{r+\delta+\mu(M)+2\sigma}{(1-\varepsilon)(r+\delta+\mu(M))+2\sigma}\right)\underline{p}_B(M) \tag{B.7}$$

$$\begin{aligned}\underline{p}_{WC}(\varepsilon,M) &= \frac{R(M)(r+\delta+2\sigma+\mu(M))}{(1-\varepsilon)(r+\delta+\mu(M))+2\sigma} \\ &= \underline{p}_{BW}(\varepsilon,M)-\frac{c[(r+\delta)(r+\delta+2\sigma)+(r+\delta+\sigma)\mu(M)]}{\mu(M)[(1-\varepsilon)(r+\delta+\mu(M))+2\sigma]}\end{aligned} \tag{B.8}$$

Sorting cutoffs — Solving for $\partial \mathbb{E}_s(p,\varepsilon,M)/\partial p = 0$ and $\partial \mathbb{E}_s(p,\varepsilon,M)/\partial \varepsilon = 0$, we find:

$$\begin{aligned}
p_B^*(\varepsilon,M) &= p_B^*(M) = R(M) - c + \tfrac{\mu(M)(r+\delta+\sigma+\mu(M))R'(M)}{(r+\delta)\mu'(M)} && \text{(B.9)}\\
p_W^*(\varepsilon,M) &= \tfrac{(r+\delta+2\sigma)R(M)-c(r+\delta+\sigma)}{(1+\varepsilon)(r+\delta)+2\sigma} + \tfrac{\mu(M)[(r+\delta)(r+\delta+2\sigma)+(r+\delta+\sigma)\mu(M)]}{(r+\delta)[(1+\varepsilon)(r+\delta)+2\sigma]} && \text{(B.10)}\\
p_C^*(\varepsilon,M) &= \frac{1}{1+\varepsilon}\left(R(M) - c + \tfrac{\mu(M)(r+\delta+\sigma+\mu(M))R'(M)}{(r+\delta)\mu'(M)}\right) && \text{(B.11)}\\
\varepsilon_W^*(p,M) &= -\tfrac{c+p-R(M)}{p} - \sigma\left(\tfrac{c+2(p-R(M))}{p(r+\delta)}\right) && \text{(B.12)}\\
&+ \tfrac{R'(M)}{\mu'(M)}\left(\tfrac{(r+\delta)(r+\delta+2\sigma)\mu(M)+(r+\delta+\sigma)\mu^2(M)}{p(r+\delta)^2}\right)\\
\varepsilon_C^*(p,M) &= -\tfrac{c+p-R(M)}{p} - \tfrac{R'(M)}{\mu'(M)}\left(\tfrac{(r+\delta+\sigma+\mu(M))\mu(M)}{p(r+\delta+\sigma)}\right) && \text{(B.13)}
\end{aligned}$$

B.2. Proofs

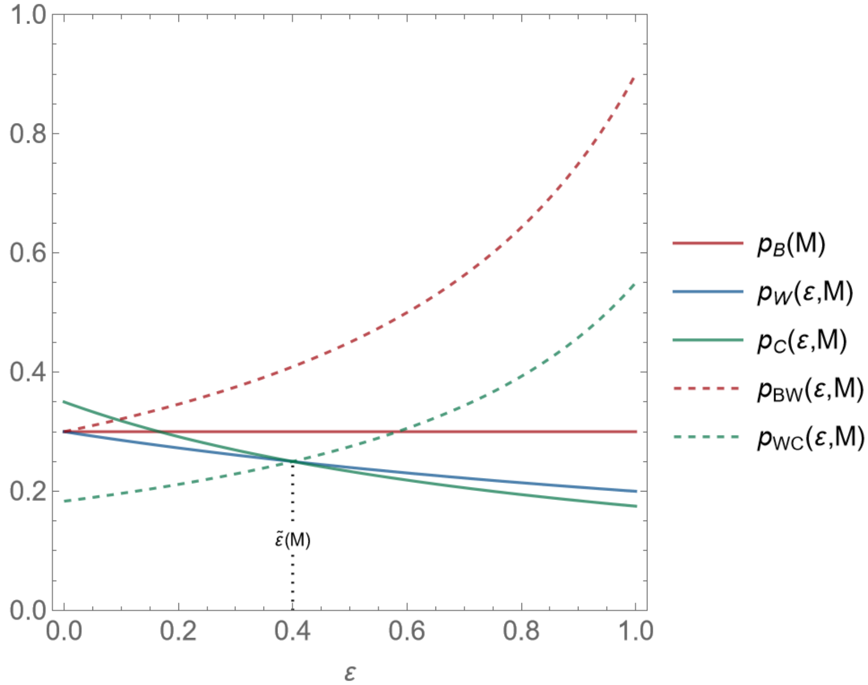
Proof of Proposition 1 — Result 1.1 stems from the facts that $\partial \underline{p}_{WC}(\varepsilon,M)/\partial\varepsilon > 0$ and $\partial \underline{p}_{C}(\varepsilon,M)/\partial\varepsilon < 0$ and that the selection cutoff for strategy C is the lowest, as long as $\varepsilon \geq \tilde{\varepsilon}(M)$. Result 1.2 stems from the fact that $\partial^2 \underline{p}_{WC}(\varepsilon,M)/\partial\varepsilon\partial\varepsilon > 0$.

Proof of Proposition 2 — Result 2.1 is obtained by noticing that, under Assumptions 1 and 2, $\partial \underline{p}_{BW}(\varepsilon,M)/\partial M > 0$. Thus, the are of region B decreases with density. Moreover, under Assumption 2, $\partial \underline{p}_{W}(\varepsilon,M)/\partial M > 0$. In addition, under no assumption, $\partial[\underline{p}_{BW}(\varepsilon,M) - \underline{p}_{WC}(\varepsilon,M)]/\partial M < 0$. 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, $\partial[\underline{p}_{WC}(\varepsilon,M) - \underline{p}_{C}(\varepsilon,M)]/\partial M > 0$. Thus, the area of region C increases with density. Result 2.2 can be derived by observing that the productivity-volatility substitution for selection is represented by $\underline{p}_{W}(\varepsilon,M)$ for $\varepsilon \in [0,\tilde{\varepsilon}(M)]$ and $\underline{p}_{C}(\varepsilon,M)$ for $\varepsilon \in [\tilde{\varepsilon}(M),1]$. Then, under Assumption 2, $\partial^2\underline{p}_{W}(\varepsilon,M)/\partial\varepsilon\partial M < 0$ and $\partial^2\underline{p}_{C}(\varepsilon,M)/\partial\varepsilon\partial M < 0$. Thus, in denser cities, volatility and productivity are better substitutes for lowering the selection of firms.

Proof of Proposition 3 — Result 3.1 stems from the fact that under Assumption 3, we can show that $\forall s \in \{B, W, C\}, \partial p_s^*(\varepsilon, M)/\partial M > 0$ and $\forall s \in \{W, C\}, \partial \varepsilon_s^*(p, M)/\partial M > 0$. Therefore, more productive and more volatile firms sort into denser cities. In addition, we can also show that $\forall s \in \{W, C\}, \partial^2 p_s^*(\varepsilon, M)/\partial M \partial \varepsilon < 0$ and $\partial^2 \varepsilon_s^*(p, M)/\partial M \partial p < 0$. 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 $\frac{\partial p_B^*(M)}{\partial M} > \frac{\partial p_W^*(\varepsilon,M)}{\partial M} > \frac{p_C^*(\varepsilon,M)}{\partial M}$. 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.

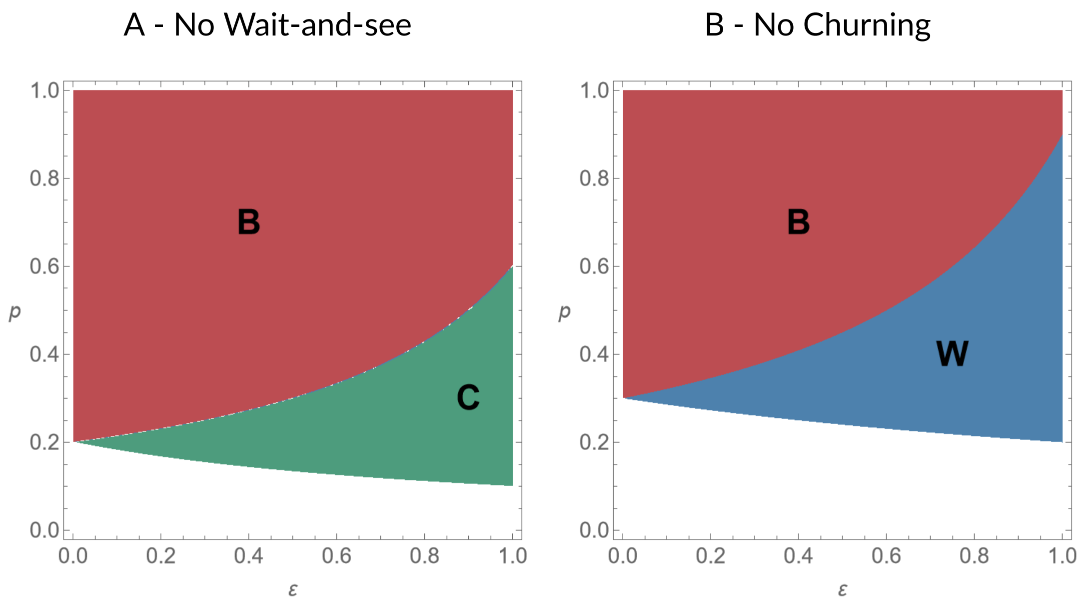
B.3. Additional illustrations

Figure B.1 — Selection and switching cutoffs



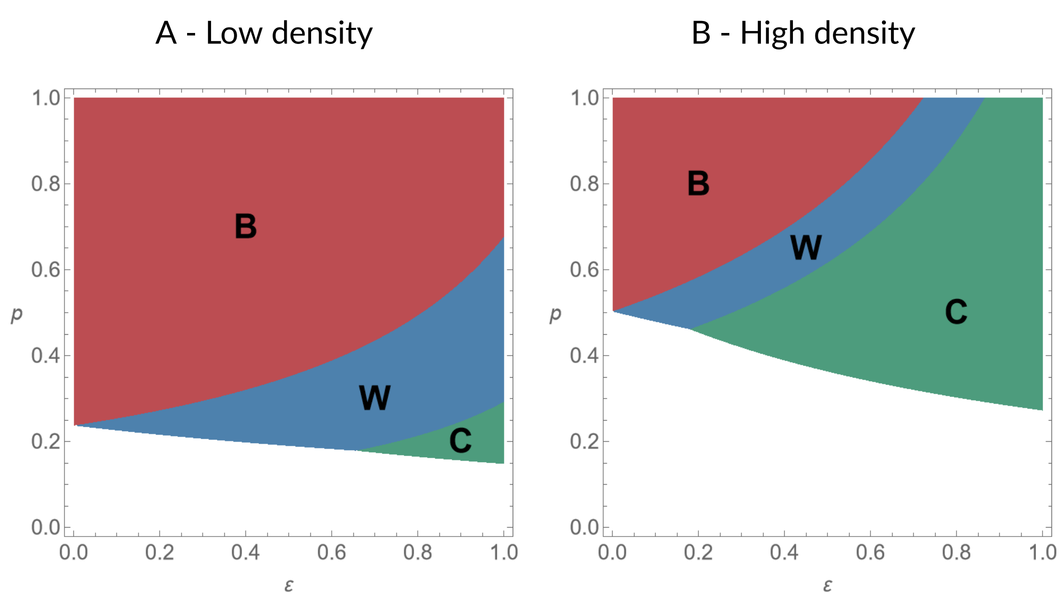
Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = 0.02$, $R(M) = 0.2$, $\overline{p} = 1$. The figure represent the selections and switching cutoffs as a function of volatility.

Figure B.2 — Adopted strategies when one strategy disappears



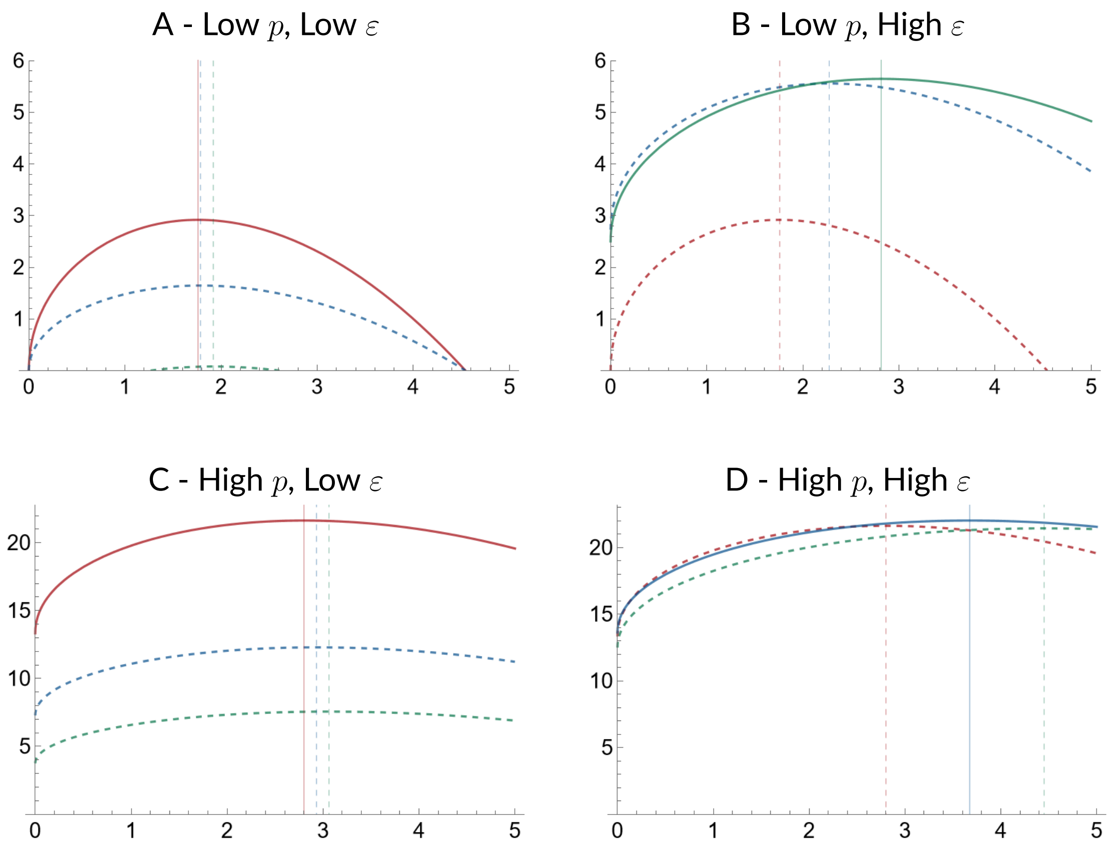
Calibration: Panel A: same as Figure 4, with $c = 0.001$. Panel B: same as Figure 4, in a model featuring positive firing costs $\chi = 5$. The figures represent the set of (ε, p) combinations associated with each adopted strategy. The blank sections correspond to combinations that are not feasible, regardless of the strategy.

Figure B.3 — Adopted strategies for two levels of density



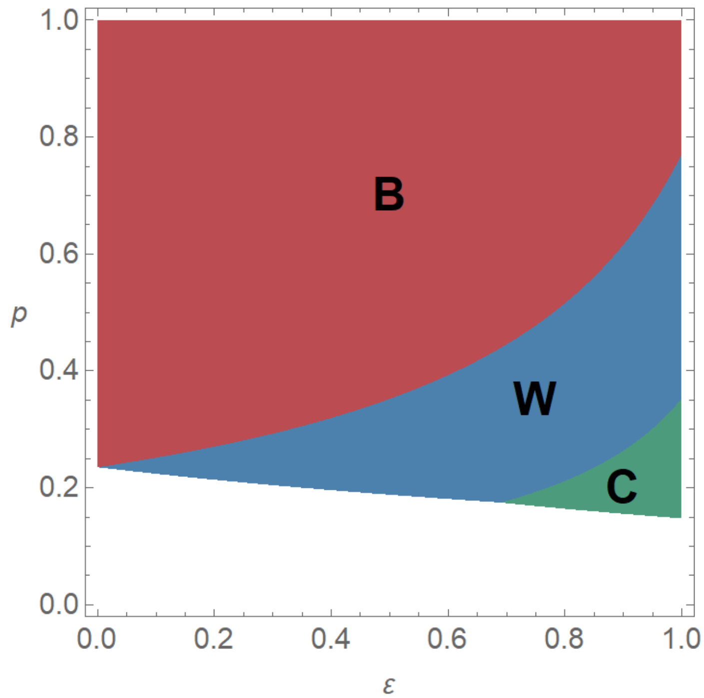
Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. Panel A: $M = 2$; Panel B: $M = 8$. The figures represent the set of (ε, p) combinations associated with each adopted strategy. The blank sections correspond to combinations that are not feasible, regardless of the strategy.

Figure B.4 — Expected profit as a function of density



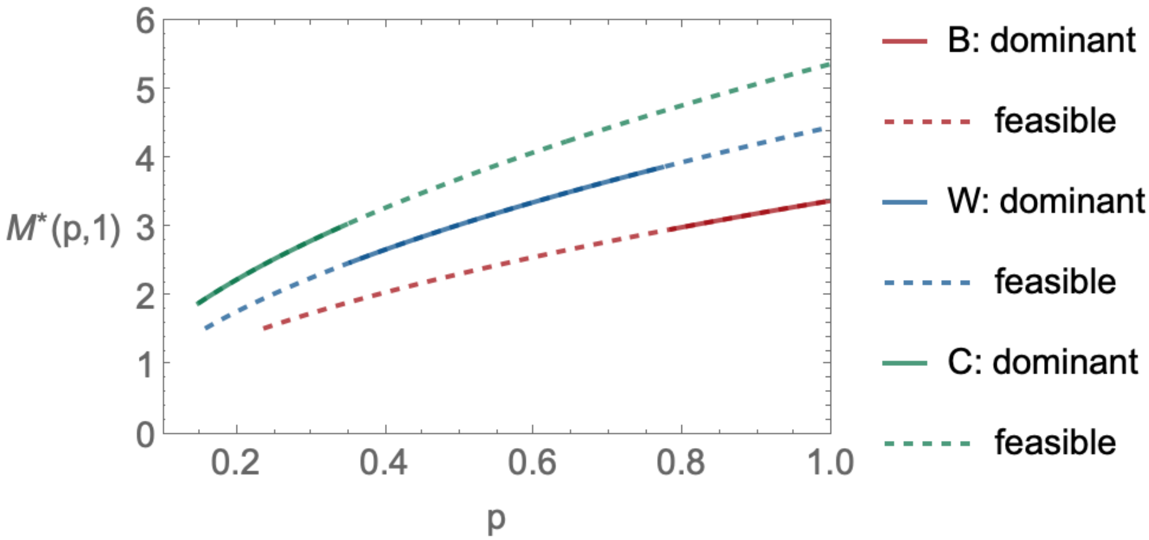
Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. Expected profit $\mathbb{E}_s(p, \varepsilon, M)$ as a function of density M, with B in red, W in blue and C in green. The vertical lines show the optimal density (found by numerical search). The plain line represents the adopted strategy and the dashed lines represent feasible strategies. $(p, \varepsilon) \in \{0.3, 0.7\} \times \{0, 1\}$.

Figure B.5 — Adopted strategies under optimal city choice



Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. The figure represents the set of (ε, p) combinations associated with each adopted strategy. The blank section corresponds to combinations that are not feasible, regardless of the strategy. Density is given by $M = M^*(p, \varepsilon)$ found by numerical search.

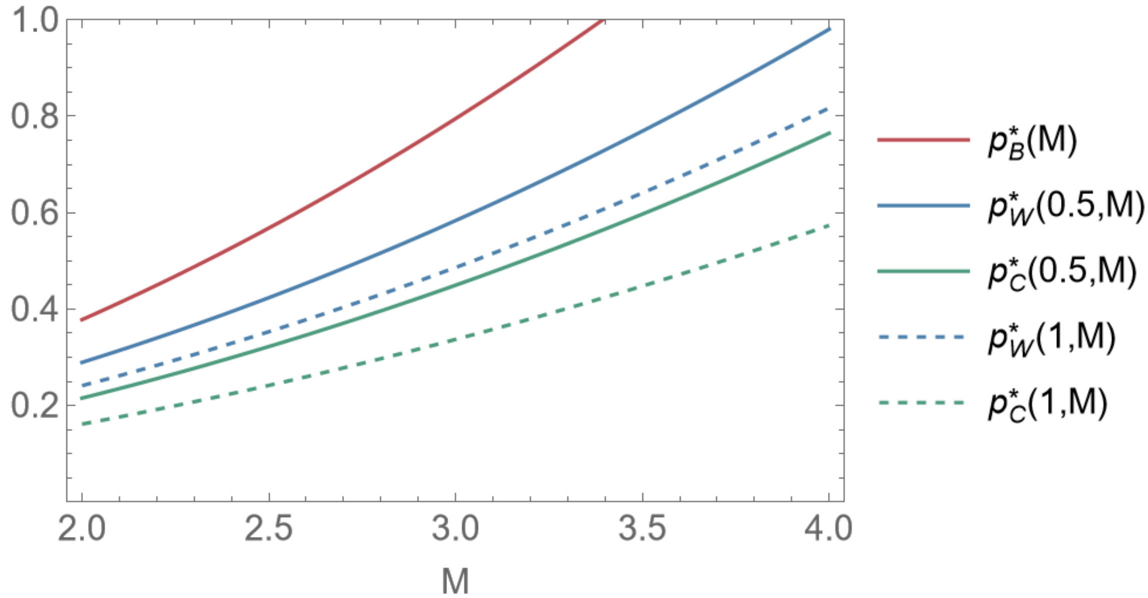
Figure B.6 — Optimal density by strategy for the most volatile firms



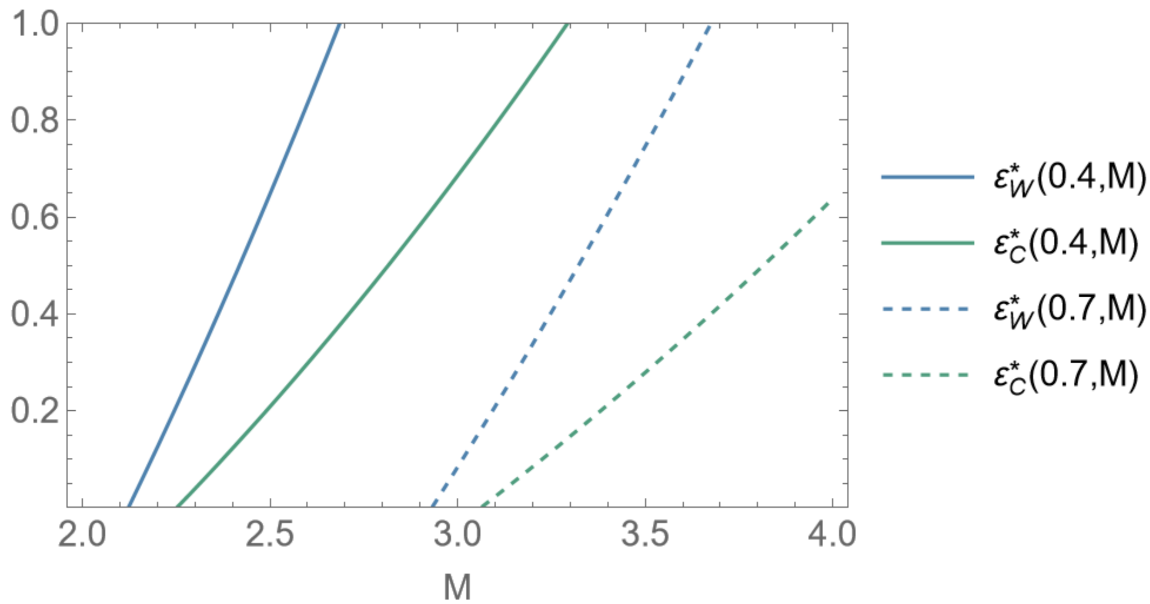
Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. The figure represents the optimal city choice (found by numerical search) as a function of productivity, for the most volatile firms $(\varepsilon = 1)$.

Figure B.7 — Sorting for each strategy

A - Sorting by productivity



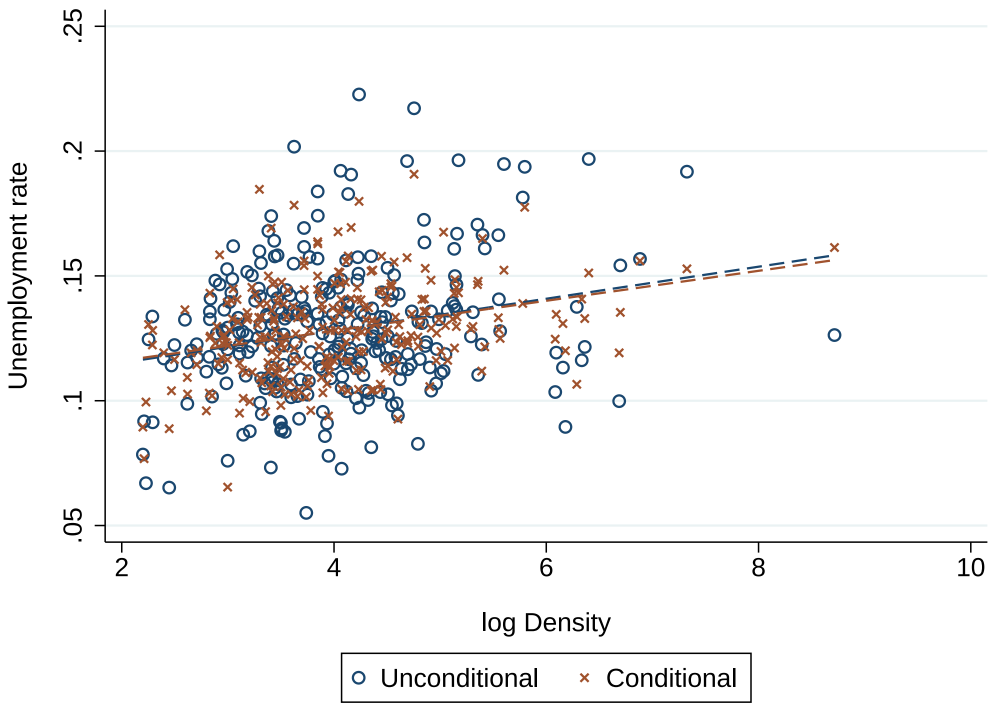
B - Sorting by volatility



Calibration: $c = 0.1$, $\sigma = 0.01$, $r = 0.01$, $\delta = 0.01$, $\mu(M) = \sigma + B\sqrt{M}$, $R(M) = c + BM^2$, $B = 5/1000$, $\overline{p} = 1$. Panel A: The figure represents the sorting cutoffs $p_s^*(\varepsilon, M)$ as a function of density for two levels of volatility $\varepsilon \in \{0.5, 1\}$. Panel B: The figure represents the sorting cutoffs $\varepsilon_s^*(p, M)$ as a function of density for two levels of productivity $p \in \{0.4, 0.7\}$. Note that these cutoffs are not represented conditionally on selection. Therefore, the strategies may not be feasible for low values of p or ε.

C — Additional tables and figures

Figure C.1 — Unemployment rate and density



Notes: The figure shows the unemployment rate of the working-age population (aged 15-54) by commuting zone as a function of its (working-age) population density. In red, we provide the correlation after controlling for the share of university graduates in the population above 15, the share of managers among employed workers, the shares of old and young workers in the working-age population, and 22 region fixed effects. Source: 2018 Census