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# City Size and the Risk of Being Unemployed. Job Pooling vs. Job Competition

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## Abstract

We study the relationship between city size and the risk of being unemployed. We introduce a new mechanism, *job pooling*, as a source of agglomeration economies in a model of risk sharing with an imperfect labor market and risk-neutral agents. Despite competition across workers for jobs in the largest cities (*job competition*), workers tend to be located in large cities because tight labor markets yield income gains from the sharing of firms among workers that do not know *ex ante* the negotiated wage rates (*job pooling*). The covariance between the probability of being unemployed and firm-specific wage shocks decreases with the number of workers. This explains why larger cities exhibit a higher unemployment rate on average and weaker fluctuations. From French data, we find that the positive covariance between the unemployment rate and local wages decreases with city size. We also show that moving from an area in the first quartile of density to the last quartile translates into an increase in unemployment of 14 %. In contrast, the elasticity of unemployment fluctuations with respect to employment density is negative: moving from an area in the first quartile of density to the last quartile translates to a decrease in our unemployment fluctuation index of 25 %.

**Keywords:** Job Pooling; Risk Sharing; Agglomeration; Unemployment rate; Unemployment fluctuation

**JEL Classification:** R23 ; J61

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# 1 Introduction

We investigate the relationship between city size and the risk of being unemployed. It is well documented that the unemployment rate varies substantially across cities in many countries (Elhorst, 2003). For example, in France in 2003, the unemployment rate in the jurisdiction *Les Herbiers* (a small locality in the west) was 3.8%, while it reached 15% in the city of Sète (a medium-sized locality in the south). Intriguingly, the variance in unemployment differs across labor market areas. For example, despite the crisis, unemployment in Paris remained nearly unchanged at approximately 8% between 2003 and 2017 (with a relatively low variance of 0.62). In contrast, it has varied substantially in the city of Morteau (a small jurisdiction located in the east); there, local unemployment peaked at 7.7% in 2010, while it was 3.5% two years earlier.

In this paper, we propose a new framework for understanding the impact of city size on the level and variance of unemployment rates. To identify the mechanisms at work, we first develop a model of agglomeration and risk sharing with an imperfect labor market and risk-neutral workers. Our analysis relies on the following trade-off. On the one hand, fierce competition among workers for employment in highly populous cities discourages them from agglomerating in the absence of uncertainty (the *job competition effect*). For a given number of firms, workers would rather face less competition for the available jobs. On the other hand, workers tend to be located in large cities because a tight labor market yields income gains from the sharing of firms among workers who do not know *ex ante* the negotiated wage rates in each firm (the *job pooling effect*). This result arises from the fact that the covariance between the probability of being unemployed and firm-specific wage shocks is decreasing in the number of workers. The basic idea is that agglomerated places reduce uncertainty over future conditions in the labor market. The uncertainty endured in the labor market drives people to more agglomerated places. This inflow of labor into dense areas increases unemployment in cities. It follows that a larger city size induces a higher unemployment rate on average but reduces its variance. Our job pooling model can be regarded as the worker-side version of the labor pooling model (Krugman, 1991).

We confront our model predictions with French data. First, we use quarterly local unemployment data to assess the impact of city size on unemployment disparities. Our empirical investigation corroborates our theoretical findings about the relationship between city size and unemployment: a larger city size increases the unemployment rate but lowers its variability. We show that moving from an area in the

first quartile of density to the last quartile translates into an increase in unemployment of 14% and to a decrease in our unemployment fluctuation index of 25%. In a second step, we investigate the relationship between the unemployment rate and wages by exploiting French administrative data. In accordance with our model, we find that the positive covariance between wages and unemployment rates declines sharply with city size.

The crucial empirical issue is related to possible endogeneity biases. Our empirical specifications may be biased due to reverse causality between our dependent variables and urban density. To address this issue, we use instrumental variables. We instrument city size with two sets of variables: historical population size and soil-type characteristics. Our results are consistent across specifications and confirm all our theoretical predictions, showing that job pooling is a relevant source of agglomeration in an imperfect labor market context.

**Related literature.** Zenou (2009) offers different frameworks in which unemployment prevails because of search frictions, a minimum wage or efficiency wages. However, he focuses on the spatial variation in unemployment within cities. In our case, we study the inter-city distribution of the unemployment rate. Urban economic theory is surprisingly silent on the large and persistent differences across cities in the level of unemployment rates. As emphasized by Combes and Gobillon (2015), the impact of city size on unemployment has received little attention in the literature.

Search and matching models exploring the link between city size and unemployment are scarce and do not deliver a clear message (Wheeler, 2008). Previous works examining the relationship between unemployment duration and city size in a job-search framework find a negative relationship between unemployment and local density (Alperovich (1993); Gan and Zhang (2006)). Using Italian data, Di Addario (2011) shows that local market size increases job seekers' chances of finding employment (conditional on having searched). However, Petrongolo and Pissarides (2001), in their seminal review of the literature on the matching process, show that the vast majority of empirical work on matching functions supports constant returns to scale. The likelihood of finding employment is affected only by the ratio between unemployment and vacancies, not by the size of the labor market. Baum-Snow and Pavan (2012) allow for job-to-unemployment transitions in a model that incorporates endogenous migration between small, medium, and large cities. They find that match quality contributes little to the observed city size premium. Using a semi-structural approach, Petrongolo and Pissarides (2006) show that agglomeration increases the likelihood of receiving a job offer. Nevertheless, local market size does not influence the overall job-finding rates because the likelihood of acceptance decreases as

the market size increases. Hence, search and matching models reveal a non-positive effect of city size on unemployment, whereas our estimations reject this prediction.

By considering unemployment, our paper extends the literature that emphasizes the role played by *risk sharing* in the agglomeration process. We know from urban economics that firms agglomerate to exploit scale economies associated with a large labor pool. Since the seminal work of Marshall (1890), risk-sharing mechanisms have been regarded as a source of industry agglomeration. Krugman (1991) formalizes this idea for industries producing under decreasing returns to scale and that are affected by specific idiosyncratic shocks. Overman and Puga (2010) show that under the assumption of profit convexity in the establishment-specific shock, firms that experience considerable variability in their production are prompted to locate in agglomerated areas.<sup>1</sup> However, in models of labor pooling, wage adjustments are free and instantaneous in response to shocks such that there is no unemployment in equilibrium.

To the best of our knowledge, our paper is the first to consider unemployment in a model of agglomeration and risk sharing. We analyze how risk-sharing mechanisms shape equilibrium unemployment and its variability. Instead of the competitive wage setting assumption usually made in labor pooling models, we allow for a non-competitive labor market, thus implying unemployment. We assume that unions and firms bargain over wages and that firms unilaterally choose employment levels to maximize profits. In equilibrium, involuntary unemployment arises. We show that denser areas experience both lower fluctuations in their unemployment rate and higher unemployment rates.

The paper is organized as follows. In the next section, we present our main data and report simple correlations between city size, the level of the unemployment rate, and fluctuations in the unemployment rate. In Section 3, we develop our framework to deliver some predictions on the relationship between agglomeration and unemployment. In Section 4, we first present our strategy to evaluate the causal effect of city size on the risk of being unemployed; then, we display our empirical results obtained using French data. The final section concludes the paper.

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<sup>1</sup>Some papers extend Krugman's models; for instance, Combes and Duranton (2006) formalize a trade-off between the benefits of labor pooling (risk sharing among firms) and the cost of labor poaching (*i.e.*, competition among firms to attract key workers). However, Andini et al. (2013) find weak evidence for the role of labor pooling in workforce agglomeration. They conclude that it seems unlikely that labor pooling accounts for a substantial share of the benefits of agglomeration.

## 2 Local unemployment and city size: a glance at the data

Our main dataset consists of quarterly unemployment series for 304 French employment areas computed by the French National Institute of Statistics for the period 2003-2017 (we exclude from our sample the French overseas departments).<sup>2</sup> The employment areas (*'zones d'emploi'* in French) are defined by the French Institute of Statistics as 'independent' labor markets. An employment area is the geographical unit within which most of the labor force lives and works and in which establishments can find the majority of the labor force necessary to occupy the offered jobs. This spatial nomenclature exhaustively covers French territory. Our outcome of interest, the local population density, is computed by dividing the local population by the surface of an employment area.<sup>3</sup>

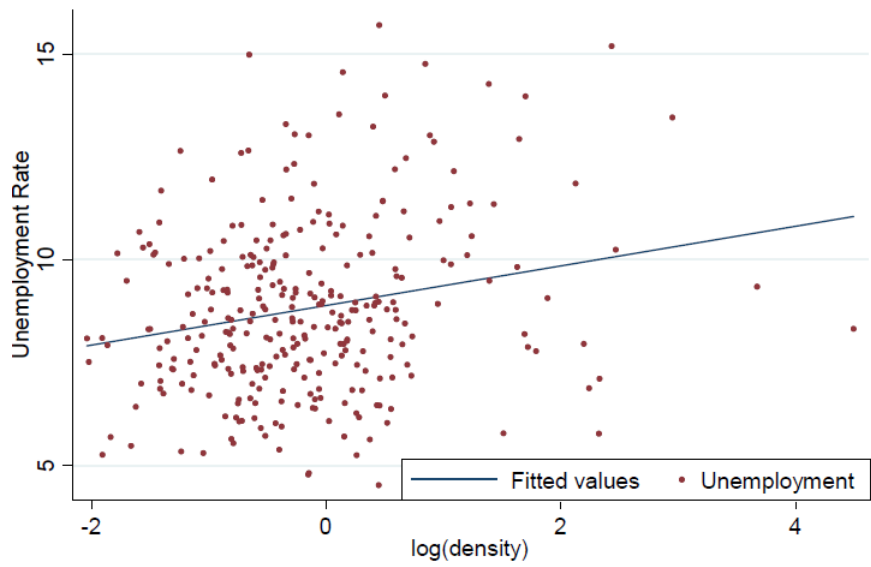
Similar to other economies in Europe, the French labor market is characterized by considerable local fluctuations in unemployment rates; indeed, unemployment varies across employment areas by a factor of four (for instance, 4% in Houdan and 17% in Agde-Pézenas). When we focus on metropolitan areas such as Paris, Marseille, Lyon, and Toulouse, we observe that French cities experience both relatively high unemployment and low fluctuations in their unemployment rates. This observation is supported by Figures 1 and 2. These figures reveal a positive relationship between employment density and unemployment and a negative relationship between density and unemployment volatility.

An examination of this descriptive evidence provides the first insight concerning the relationship between city size and unemployment. The next section provides a new theoretical framework for understanding the impact of city size on the level and variance of unemployment rates.

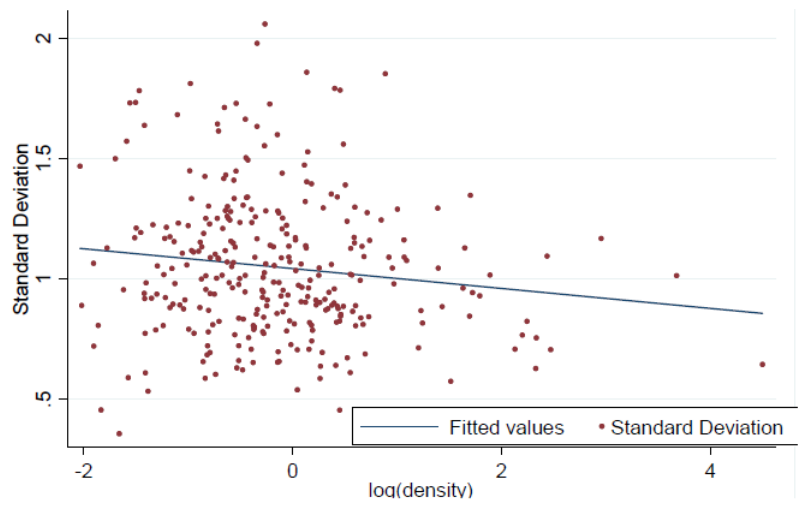
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<sup>2</sup>The unemployment rate corresponds to the ratio between the local number of unemployed persons and the local labor force. The French National Institute of Statistics exploits the Labor Force Survey to calculate the unemployment rate following the methodology of the International Labour Organization.

<sup>3</sup>The data come from the national survey conducted by the National Institute of Statistics and Economic Studies.



**Figure 1.** City size and unemployment rate (2003-2017)



**Figure 2.** City size and unemployment standard deviation (2003-2017)

### 3 Job pooling, risk sharing and unemployment

By considering unemployment, our paper extends the literature that emphasizes the role played by labor pooling in the agglomeration of firms and workers. Recall that the central idea developed in labor pooling models with risk sharing (Krugman, 1991) is that firms tend to be located in agglomerated areas because agglomeration yields profit gains from the sharing of labor among firms that do not know *ex ante* how much of the labor they will hire. Such a result emerges because the covariance between local wages and firm-specific productivity shocks is decreasing in the number of firms. Our approach differs from such models in two ways.

First, in models of labor pooling, wage adjustments in response to shocks are free and instantaneous, such that there is no unemployment in equilibrium. Instead of a competitive labor market, we assume that imperfect competition prevails in local labor markets. More precisely, we assume that each local labor market is unionized, implying some rigidity in wage setting and unemployment. Bargaining occurs between individual firms and individual unions (a decentralized bargaining regime).<sup>4</sup>

Second, in models of labor pooling, technology shocks drive local economic fluctuations. However, in accordance with recent developments on the sources of unemployment fluctuations, we consider labor market shocks instead of productivity shocks. Indeed, the theories relying on technology shocks as the driving forces of unemployment fluctuations have been challenged by several studies (Chari et al. (2007), Hall (1997), Hall (2005), Shimer (2005) and Shimer et al. (2010)). The recent literature has found that labor market shocks are central to understanding movements in unemployment. More precisely, shocks to the bargaining power of workers are shown to be important determinants of business cycles. Galí et al. (2012) underline that wage markup shocks are a major determinant of output and employment fluctuations.<sup>5</sup> Using a different empirical strategy, Drautzburg et al. (2017) also em-

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<sup>4</sup>As we test our theoretical predictions using French data, we could wonder whether wage bargaining occurs at the firm level in France. In France, the predominant level of wage bargaining is most adequately described as a combination of industry and company/plant level, with an important share of employees being covered by company bargains (OECD Employment Outlook 2004; see Table 3.5, page 151). French institutions allow collective bargaining to occur at the national, industry and firm levels. Collective agreements are not permitted to discriminate between union members and non-unionized workers. Although industry-level bargaining is an important level for collective bargaining in France, collective bargaining at the firm level also plays a key and increasing role. Employers are required to negotiate annually on pay, working time and other issues, as long as firm-level agreements do not provide worse terms and conditions than those set by the appropriate industry agreements. In addition, legislation introduced in 2004 has made it easier for firm agreements to diverge from industry-level agreements in areas where this is not specifically prohibited by industry agreements (e.g., minimum wage rates, where divergence is prohibited). More recently, 2008 legislation gave primacy to firm-level, rather than industry-level, agreements in the area of working time.

<sup>5</sup>In New Keynesian models, shocks to the wage equation are named wage mark-up shocks,



phasizes the central role played by bargaining shocks in output and unemployment fluctuations. More recently, by disentangling labor supply shocks from wage bargaining shocks, Foroni et al. (2018) show that the latter shocks are important drivers of output and unemployment in both the short run and the long run.

The timing of the model is as follows. Workers and firms choose the city in which they will reside without knowing their bargaining power but anticipating (with rational expectations) the wage negotiation. Hence, the location choice of workers (resp., firms) is based on the difference in expected income (resp., expected profit) across cities. Indeed, we assume that wage rates are revealed after location choices have been made to account for the relative inertia of geographical mobility compared to labor market fluctuations. Hence, we assume that workers are stuck in their initial locations (determined in the first stage) and cannot relocate to another city to capture the relative inertia of residential choice compared to the labor markets.

### 3.1 Wage setting and labor demand

To ease the notational burden, we describe the economy of a single city. We assume that all firms produce a standardized product and that prices are set equal to unity. Labor is the only production factor. Each worker supplies one unit of labor. The profit of firm  $i$  is given by  $\pi_i(\ell_i) = q_i(\ell_i) - \omega_i \ell_i$ , where  $\ell_i$  is the quantity of labor,  $\omega_i$  is the wage rate, and  $q_i(\ell_i)$  is the output. A firm's technology is described by the following production function:  $q_i(\ell_i) = \alpha \ell_i - \ell_i^2/2$ . Therefore, there are no scale economies in production. We consider a decentralized and uncoordinated wage-setting structure in which firms and firm-specific unions bargain bilaterally over the match-specific wage rate. Since workers are identical, we assume that available jobs are allocated randomly among them.

Let  $\gamma_i \in [0; 1]$  denote the bargaining power of firm  $i$ , which is firm specific. We assume that there are no search costs for finding better matches. We also assume that unions have a minimum acceptable wage given by  $\bar{\omega}$ .<sup>6</sup> The bargained solution between a union and a firm then maximizes the following Nash product:

$$\mathcal{N} = \pi_i^{\gamma_i} \left[ \ell_i^\theta (\omega_i - \bar{\omega})^{1-\theta} \right]^{1-\gamma_i}, \quad (1)$$

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whereas in search and matching models, they are named wage bargaining shocks. Wage mark-up shocks can be interpreted as variations in the bargaining power of workers (Chari et al., 2009).

<sup>6</sup>In the French context,  $\bar{\omega}$  can be interpreted as a wage floor set by industry-level agreements. This negotiated industry-level wage floor is used by firms as a reference for their wage policy.

where the union is specified by the Stone-Geary-type utility function with  $\theta \in [0, 1]$ . The parameter  $\theta$  represents the importance of wages relative to employment for the union. This implies that firms and unions bargain over both wages and employment. Without loss of generality, we assume in this section that  $\theta = 0$ . We detail the case in which  $\theta > 0$  in Appendix A.1, which leads to similar conclusions. Hence, in this section, we assume that firms unilaterally choose employment levels to maximize their profits (*i.e.*, right-to-manage models). The firm is assumed to have free choice in employment, but there is bargaining between the firm and the union over wages. Each firm chooses how many workers to hire by taking wages as given and after experiencing their firm-specific productivity. From the profit-maximizing first-order conditions for labor demand for each firm, we obtain

$$\ell_i = \alpha - \omega_i. \quad (2)$$

Inserting (2) into the profit expression implies

$$\pi_i(\ell_i) = \frac{(\alpha - \omega_i)^2}{2}. \quad (3)$$

Maximizing the Nash product  $\mathcal{N}$  with respect to the wage rate yields the equilibrium wage:

$$\omega_i = \alpha - \varphi_i(\alpha - \bar{\omega}), \quad (4)$$

with  $\varphi_i \equiv \frac{2\gamma_i}{1+\gamma_i} \in (0, 1)$ . We assume that  $\varphi_i = \varphi + \varepsilon_i$ , where  $\varphi$  is common to all matches, while  $\varepsilon_i$  is a firm-specific bargaining power shock. Firm-specific shocks are identically and independently distributed over  $[-\varepsilon, \varepsilon]$  with mean 0 and variance  $\mathbb{V}(\varepsilon)$ . As expected, wages depend negatively on the bargaining power of firms, while a higher reservation wage increases the equilibrium wage. We assume that the support of the distribution of bargaining power shocks is not too large relative to labor productivity (captured by  $\alpha$ ) such that employment and wages in all firms are non-negative in equilibrium.

Firms observe the wage ensuing from negotiations and decide how much labor to hire from the local labor pool. Each establishment hires workers until the marginal product of labor equals wages. Using (2) and (4), we obtain the labor demand arising from firm  $i$ :

$$\ell_i = \varphi_i(\alpha - \bar{\omega}). \quad (5)$$

Let  $n$  denote the number of firms. The aggregate demand for labor is equal to

$$\sum_{i=1}^n \ell_i = n\varphi(\alpha - \bar{\omega}) + (\alpha - \bar{\omega}) \sum_{i=1}^n \epsilon_i. \quad (6)$$

### 3.2 Expected income, unemployment risk, and city size

A typical worker earns  $\omega_i$  when employed and enjoys unemployment insurance benefits  $b$  when unemployed. We assume that  $b$  is constant across markets and independent of market returns. Workers are risk neutral and choose their city by comparing their expected incomes, given by

$$y^e = \mathbb{E}(p \times \omega) + \mathbb{E}(1 - p) \times b, \quad (7)$$

where  $p$  is the probability of finding a job. We assume that  $b$  is set equal to 0 for simplicity. By the law of large numbers, the probability of obtaining a job is equal to  $p = \sum_{i=1}^n \ell_i / L$ , where  $L$  is the total labor force in the city. Further,  $\mathbb{E}(p \times \omega) = \mathbb{E}(p) \times \mathbb{E}(\omega) + \text{Cov}(\omega, p)$ . The use of (4) implies that  $\mathbb{E}(\omega) = \alpha - \varphi(\alpha - \bar{\omega})$ , and the use of (6) yields  $\mathbb{E}(p) = \frac{n}{L} \varphi(\alpha - \bar{\omega})$ . In addition, it is straightforward to verify that the covariance is given by  $\text{Cov}(\omega, p) = -\frac{(\alpha - \bar{\omega})^2}{L} \mathbb{V}(\epsilon) < 0$ . Therefore, expected income is equal to

$$y^e = [\alpha - \varphi(\alpha - \bar{\omega})] \varphi(\alpha - \bar{\omega}) \frac{n}{L} - \frac{(\alpha - \bar{\omega})^2}{L} \mathbb{V}(\epsilon). \quad (8)$$

It follows that, for a given population size, expected income increases with the number of firms. Hence, workers are attracted by cities endowed with a large number of firms. However, an increasing population has an ambiguous effect on expected income because of the uncertain bargaining power. Under certainty, income decreases with  $L$  for a given  $n$ . This is due to *job competition* among workers. In this case, the inter-city distribution of workers would follow the spatial allocation of firms ( $n/L$ ) and would be constant across cities. However, the negative effect of an increase in local labor supply is weakened under uncertainty, as the covariance between the local wage and the probability of being employed is negative and decreases with population size. This is captured by the second term on the right-hand side of (8)  $((\alpha - \bar{\omega})^2) \mathbb{V}(\epsilon) / L$ . *For a given ratio of firms to workers, the expected income is higher in a more populous city.* Hence, under wage uncertainty, workers have an

incentive to agglomerate. This is the *job pooling* effect, which can be regarded as the worker-side version of the labor pooling model. Each worker benefits from sharing the local labor market with more labor suppliers under uncertainty in wage setting. It also appears that the benefits of job pooling will be greater as the heterogeneity of firm-specific shocks increases.

We now analyze the relationship between population size and unemployment risk. The expected unemployment rate  $E(u)$  is given by

$$\mathbb{E}(u) = 1 - \frac{\varphi(\alpha - \bar{\omega})}{L/n} = 1 - \frac{\varphi(\alpha - \bar{\omega})}{\Gamma} \left[ y^e + \frac{(\alpha - \bar{\omega})^2 \mathbb{V}(\epsilon)}{L} \right], \quad (9)$$

and its variance is equal to

$$\mathbb{V}(u) = \frac{(\alpha - \bar{\omega})^2}{L/n} \mathbb{V}(\epsilon) = \frac{(\alpha - \bar{\omega})^2}{\Gamma} \left[ y^e + \frac{(\alpha - \bar{\omega})^2 \mathbb{V}(\epsilon)}{L} \right] \mathbb{V}(\epsilon). \quad (10)$$

with  $\Gamma \equiv [\alpha - \varphi(\alpha - \bar{\omega})]\varphi(\alpha - \bar{\omega}) > 0$ , and where we have used (8).

Because labor mobility equalizes expected income levels across cities, we expect that a larger population size raises the unemployment rate and reduces unemployment volatility in the context of uncertain wage setting. Indeed, for a given expected income, we have  $\frac{\partial \mathbb{E}(u)}{\partial L} > 0$ , indicating that a larger city size implies a higher unemployment rate, on average, due to the job competition effect. However, for a given expected income, the variance of the unemployment rate decreases with a marginal increase in the local labor force, as  $\frac{\partial \mathbb{V}(u)}{\partial L} < 0$ . This result highlights the job pooling effect. Such a result arises from the fact that the covariance between the probability of being unemployed and wage shocks is decreasing in the number of workers. Indeed, we have

$$\text{Cov}(\omega, u) = \frac{(\alpha - \bar{\omega})^2}{L} \mathbb{V}(\epsilon) > 0. \quad (11)$$

Hence, each worker benefits from sharing her/his job market with more workers in the face of idiosyncratic shocks.

Three comments are in order. First, our results hold even if the bargaining power  $\varphi$  (common to all matches) is determined by the relative scarcity of labor. In particular, if  $\varphi$  decreases with  $n$  and increases with  $L$ , it is straightforward to verify that  $\frac{\partial \mathbb{V}(u)}{\partial L} < 0 < \frac{\partial \mathbb{E}(u)}{\partial L}$  is still valid. Second, recall that risk aversion plays no role in our framework. Because the variance of unemployment decreases with the number of workers in a city, introducing risk aversion would only reinforce the benefits ob-

tained from job pooling on the labor suppliers' side. Third, our result indicates that a higher average firm size in a city ( $L/n$ ) raises the expected unemployment rate but decreases the unemployment fluctuation. As empirical evidence shows that the average plant size per worker is positively correlated with the spatial concentration of activities (Holmes and Stevens (2002); Lafourcade and Mion (2007)), we can expect the unemployment rate (resp., unemployment volatility) to be higher (resp., lower) in larger cities. We will see below that our model yields a spatial equilibrium configuration in which the average firm size per worker is higher in cities endowed with more firms.

### 3.3 Uncertain wage setting and agglomeration

We verify whether our main results hold when individuals and firms are free to choose the city in which they settle. To keep the model analytically tractable, we extend our framework to a system of two cities,  $A$  and  $B$ . The number of firms located in city  $A$  (resp.,  $B$ ) is  $n_A$  (resp.,  $n_B$ ). The total number of firms is  $n_A + n_B = n_T$ . Similarly, the number of workers living in city  $A$  (resp.,  $B$ ) is  $L_A$  (resp.,  $L_B$ ), and their total number is  $L_A + L_B = L_T$ . Firms and workers choose their location before the idiosyncratic shocks are realized. The location of workers is driven by the inter-city difference in their expected income, while the location choice of firms is based on their expected profit  $\mathbb{E}(\pi)$  given by

$$\mathbb{E}(\pi_c) = \frac{\tilde{\alpha}^2}{2} \left[ \varphi_c^2 + \mathbb{V}(\epsilon) \right]. \quad (12)$$

with  $c = A, B$ . The expected profit of firms increases with  $\mathbb{V}(\epsilon)$  because of the convex relationship between profits and wages. We are now equipped to determine the stable spatial configurations when both workers and firms are free to choose their location.

**Exogenous bargaining power.** If the number of firms relative to workers does not impact bargaining power  $\varphi_A = \varphi_B = \varphi$ , then the spatial difference in expected income is given by

$$y_A^e - y_B^e = \Gamma \left( \frac{n_A}{L_A} - \frac{n_B}{L_B} \right) - \tilde{\alpha}^2 \mathbb{V}(\epsilon) \left( \frac{1}{L_A} - \frac{1}{L_B} \right) \equiv \Delta_L, \quad (13)$$

with  $\tilde{\alpha} \equiv \alpha - \bar{\omega} > 0$ . An equilibrium arises when no individual has an incentive to change location (or city). Some standard calculations show that  $\Delta_L = 0$  implies

$$\frac{L_A}{L_T} = \frac{1}{2} + \frac{\Gamma n_T}{\Gamma n_T - 2\tilde{\alpha}^2 \mathbb{V}(\epsilon)} \left( \frac{n_A}{n_T} - \frac{1}{2} \right) \equiv \lambda_L. \quad (14)$$

The interior equilibrium  $\lambda_L \in (0, 1)$  is stable if and only if the slope of the expected income differential  $\Delta_L$  is strictly negative in a neighborhood of the equilibrium  $\lambda_L$  (as we consider a continuum of workers). It is straightforward to check that  $\frac{\partial \Delta_L}{\partial L_A}$  evaluated at  $L_A/L_T = \lambda_L$  is negative when  $\mathbb{V}(\epsilon) < \frac{\Gamma n_T}{2\tilde{\alpha}^2} \equiv \hat{\mathbb{V}}(\epsilon)$ . When  $\mathbb{V}(\epsilon) \geq \hat{\mathbb{V}}(\epsilon)$ , all workers are located in a single city. Hence,  $L_A/L_T > n_A/n_T$  provided that  $\mathbb{V}(\epsilon) > 0$  and  $n_A/n_T > 1/2$ .<sup>7</sup> It follows that labor suppliers are attracted to places where firms are numerous when the wage rate is uncertain. In addition, higher uncertainty favors the spatial concentration of workers.

Firms reach the same level of profit regardless of their location when the bargaining power does not vary across cities (as  $\varphi_A = \varphi_B = \varphi$ ; see (12)). Consequently, their location is not driven by the spatial allocation of workers. The number of firms in each city depends on the mass of employed workers and is given by the labor market clearing condition (6). Under these circumstances, according to (14), the largest city is the city hosting the higher number of firms, as  $n_A > n_B$  implies  $L_A > L_B$  in equilibrium. Hence, as suggested above, *uncertain wage setting favors the emergence of large cities*.

Using (9) and (10), we obtain

$$\mathbb{E}(u_A) - \mathbb{E}(u_B) = \frac{\tilde{\alpha}^2 \mathbb{V}(\epsilon)}{\alpha - \varphi \tilde{\alpha}} \frac{L_A - L_B}{L_A L_B} \text{ and } \mathbb{V}(u_A) - \mathbb{V}(u_B) = \frac{[\tilde{\alpha}^2 \mathbb{V}(\epsilon)]^2}{\Gamma} \frac{L_B - L_A}{L_A L_B} \quad (15)$$

in the asymmetric equilibrium ( $y_A^e = y_B^e$ ). In addition,  $\Delta_L = 0$  implies that  $L_A/n_A > L_B/n_B$  as long as  $L_A > L_B > 0$ . Stated differently, the ratio of workers to firms is higher in the larger city. Hence, the unemployment rate is higher and its variance is lower in the largest city when the asymmetric equilibrium exists.<sup>8</sup>

<sup>7</sup>We have  $L_A/L_T = n_A/n_T$  when  $\mathbb{V}(\epsilon) = 0$ .

<sup>8</sup>This result contradicts Gan and Zhang (2006), who show that unemployment is lower in dense areas when the wage rate received by a worker decreases strongly with distance to her/his job. Our framework differs from the model developed in Gan and Zhang (2006), as they focus on frictional unemployment and consider uncertainty in the location of jobs. In our case, we consider the presence of a labor union that engages in collective bargaining on behalf of workers, which implies that the wage rate is superior to the marginal productivity of labor. This will result in a lower level of employment than the level that would occur in a competitive market. However, as in Gan and Zhang (2006), we show that the unemployment rate is less volatile in agglomerated places. This finding is in line with

**Endogenous bargaining power.** We now discuss the case in which  $\varphi$  varies across cities. If the firm's bargaining power  $\varphi$  depends negatively on  $n$  and positively on  $L$  in each city, then workers are still attracted by cities hosting a larger fraction of firms. Assume that  $\varphi_c = \frac{1}{1+n_c^{\zeta_n}/L_c^{\zeta_\ell}}$  with  $\zeta_n > 0$  and  $\zeta_\ell > 0$ .<sup>9</sup> In this case,  $\Gamma$  is specific to each city, with  $\Gamma_c = (\alpha - \varphi_c \tilde{\alpha}) \varphi_c \tilde{\alpha}$ , where  $c = A, B$ , the term within the parentheses defines the expected wage rate in city  $c$  and the term  $\varphi_c \tilde{\alpha}$  is the expected probability of being employed up to  $n_c/L_c$ . It is easy to check that  $\Gamma_A$  increases with  $\varphi_A$  and, in turn, with  $L_A$  (due to its positive effect on the probability of being employed). In other words, when the firm's bargaining power  $\varphi_c$  depends negatively on the ratio  $n_c/L_c$  in each city, agglomeration is more likely to occur. Indeed, the spatial difference in expected income is given by

$$\Delta'_L = \left( \Gamma_A \frac{n_A}{L_A} - \Gamma_B \frac{n_B}{L_B} \right) - \tilde{\alpha}^2 \mathbb{V}(\epsilon) \left( \frac{1}{L_A} - \frac{1}{L_B} \right), \quad (16)$$

which is highly nonlinear, so the interior equilibrium cannot be explicitly given and the same set of parameters may yield three stable spatial equilibria (either all workers agglomerate in one city or they distribute themselves between the two cities). Indeed, standard calculations show that  $\Delta'_L \rightarrow \infty$  when  $L_A/L_T \rightarrow 1$  and  $\Delta'_L \rightarrow -\infty$  when  $L_A/L_T \rightarrow 0$ . In addition, we have  $\Delta'_L > 0$  when  $L_A/L_T = n_A/n_T > 1/2$ , and the slope of  $\Delta'_L$  is strictly negative in a neighborhood of the interior equilibrium. It follows that when the firm's bargaining power depends negatively on the firm-worker ratio in each city, the share of workers is higher than the share of firms in the larger city.

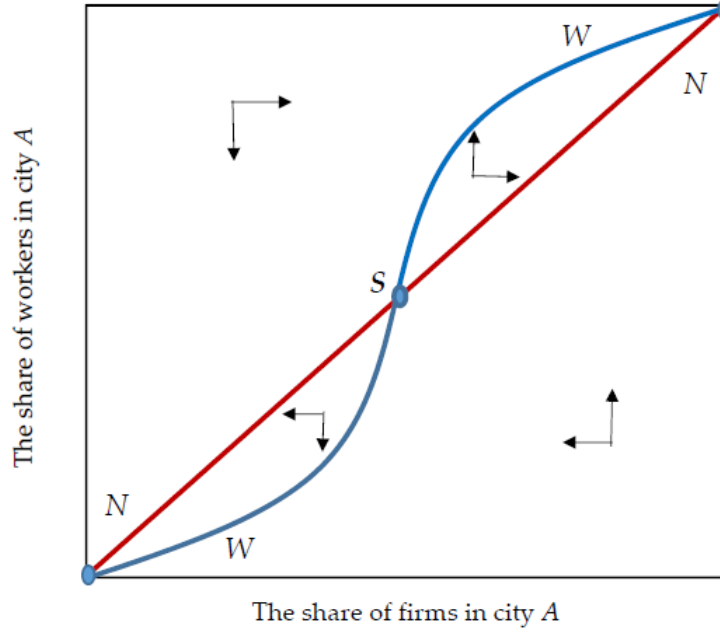
When the firm's bargaining power,  $\varphi_c$ , is endogenous, the location of firms depends on the inter-city distribution of workers. Indeed,  $\mathbb{E}(\pi_A) - \mathbb{E}(\pi_B) = 0$  implies that, for a given distribution of workers across cities,  $\varphi_A = \varphi_B$  or, equivalently,  $n_A/n_B = (L_A/L_B)^\zeta$  with  $\zeta \equiv \zeta_\ell/\zeta_n$ . Hence, some standard calculations show that  $n_A/n_T = (L_A/L_T)^\zeta [1 + (L_A/L_T)^\zeta]^{-1}$ . Therefore, for a given spatial distribution of workers, the share of firms in the more populous city is such that  $L_A/L_T > n_A/n_T > 1/2$  provided that  $\zeta < 1$ .

The determination of spatial equilibria is more complex when bargaining power depends on the ratio of firms to workers. For this case, we present the corresponding phase diagram. The two indifference loci ( $y_A^e - y_B^e = 0$  and  $\mathbb{E}(\pi_A) - \mathbb{E}(\pi_B) = 0$  when  $\zeta = 1$ ) are represented in figure 3 and labelled *WW* for workers and *NN* for

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previous models of labor pooling that state that cities reduce risk.

<sup>9</sup>It follows that  $\varphi_c \rightarrow 1$  when  $L_c \rightarrow \infty$  or  $n_c \rightarrow 0$ , while  $\varphi_c \rightarrow 0$  when  $L_c \rightarrow 0$  or  $n_c \rightarrow \infty$ .



**Figure 3.** Phase diagram for the job pooling equilibrium when  $\zeta = 1$

firms. The locus of firm indifference  $NN$  corresponds to the straight line  $n_A/n_T = L_A/L_T$ . The symmetric situation in which  $n_A = n_B$  and  $L_A = L_B$  is represented by point  $S$  in figure 3 and corresponds to interior intersection of the two indifference curves. Regarding the locus of worker indifference  $WW$ , using (16), one can show that  $WW$  is convex and lies below  $NN$  to the left of the symmetric equilibrium point  $S$ . To the right of  $S$ ,  $WW$  is concave and lies above  $NN$ . If we adopt the equilibrium concept used by Krugman (1991), who assumes that both firms and workers ignore their market impact, it follows that the symmetric equilibrium is unstable with respect to small simultaneous perturbations in the number of firms and workers (as depicted by the arrows in Figure 3). Thus, firms and workers necessarily agglomerate in a single city when  $\zeta = 1$ . It is straightforward to check that this finding is still valid when  $\zeta > 1$  or when  $\zeta$  is not too low.<sup>10</sup>

However, as noted by Ellison and Fudenberg (2003), the equilibrium concept in Krugman (1991) is not consistent with the assumption of a discrete number of firms. Firms take their market impact into account when choosing a city. Indeed, because we consider a discrete number of firms, the equilibrium condition ensuring that firms have no incentive to deviate is that a firm does not increase its expected profit by changing cities (see Ellison and Fudenberg (2003)). A firm deviating from the symmetric equilibrium reduces the bargaining power of firms and raises the ex-

<sup>10</sup>If  $\zeta$  reaches low values, then the locus of firm indifference  $NN$  is concave and lies above  $WW$  to the right of the symmetric equilibrium point  $S$ , so the symmetric equilibrium becomes stable.



pected wage that all firms, including itself, have to pay, so it cannot reach a higher expected profit by deviating from symmetric equilibrium.

According to Theorem 1 in Ellison and Fudenberg (2003), we can show that a plateau of equilibria with unequal city sizes can exist (see Appendix A.2). Under this spatial configuration, we have  $n_A/L_A = n_B/L_B$  when  $\zeta = 1$ . (see Appendix A.2). When  $\zeta < 1$ , the plateau of equilibria with unequal city sizes implies  $n_A/L_A = (L_A/L_B)^{\zeta-1}n_B/L_B$  (so that  $\mathbb{E}(\pi_A) - \mathbb{E}(\pi_B) = 0$ ). Hence, when an asymmetric equilibrium emerges, the ratio of firms to workers is higher in the more populous city provided that  $\zeta < 1$ . Nevertheless, as in Ellison and Fudenberg (2003), agglomeration of all firms and workers in a single city is also a spatial equilibrium. Such a spatial configuration emerges when the variance of shocks is high enough.<sup>11</sup>

## 4 Econometric evidence

In this section, we test the key predictions of our model. In terms of location decisions, our job pooling model and the labor pooling model developed in Krugman (1991) yield the same testable prediction: agglomeration of firms and workers is more likely to occur when the heterogeneity of firm-specific shocks is large. Nevertheless, the empirical implications derived from our model differ in terms of local unemployment. The fundamental predictions of our model relate to the relation between unemployment and city size. More precisely, our framework implies three key results: more populous cities exhibit higher unemployment rates, lower unemployment fluctuations, and a lower covariance between unemployment and wages. That is, we estimate the following:

$$Y_i = \beta_0 + \beta_1 \text{Size}_i + \epsilon_i, \quad (17)$$

where our dependent variable  $Y_i$  is either the average local unemployment rate in area  $i$  ( $\bar{u}_i$ ) or an index of unemployment volatility ( $V(u_i)$ ) or the covariance between unemployment and wages ( $\text{Corr}(u_i, \omega_i)$ ). Our variable of interest is  $\text{Size}_i$ , the city size measured as the population density in area  $i$ . The term  $\epsilon_i$  is an identically and independently distributed error term.

The main parameter of interest in equation (17) is  $\beta_1$ , the elasticity of our dependent variable with respect to city size. There are several problems associated with the identification of  $\beta_1$ , and estimating equation (17) by OLS may produce biased

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<sup>11</sup>Note that if we consider other congestion costs in our model (commuting costs or housing price), we can obtain an interior solution with partial agglomeration.

estimates. In the next subsection, we present our empirical strategy to assess the causal effect of city size on local unemployment.

## 4.1 Addressing the endogeneity of population density

Studying the relationship between unemployment and urban density is challenging. Equation 17 may be biased due to reverse causality or omitted variable bias. Indeed, if unemployment in area  $i$  increases for reasons that are uncorrelated with local density, we may expect that some people will leave area  $i$ , thus leading to a decline in local density.<sup>12</sup> Moreover, we may suspect the presence of unobservable local variables that directly affect both local density and unemployment.

We address these endogeneity issues by implementing an instrumental variable (IV hereafter) strategy.<sup>13</sup> We use history and geology as a source of exogenous variation for local density.<sup>14</sup> This strategy was first implemented by Ciccone and Hall (1993), and it is now a widespread method. Di Addario (2011) uses this approach in a very similar context: she regresses the probability of finding a job on Italian city size. To address the endogeneity of city size, she instruments agglomeration with long lagged local population and soil-type characteristics. The rationale behind this instrument is that the distribution of city size is remarkably stable over time (Bosker et al., 2008). Therefore, a long lag of population level is a good predictor of current density (*relevance conditions*). Moreover, local drivers of past agglomerations did not influence actual unemployment (*i.e., the exclusion restriction*).

Our first set of instruments is composed of historical data compiled by the French Institute for Demographic Studies (Guerin-Pace, 1993). For each five-year period between 1831 and 1982, this dataset counts the urban population. Thus, we know the municipal population for every French municipality with a population of over 5,000 inhabitants. As in Combes et al. (2010), we use the earliest census available

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<sup>12</sup>In this subsection, we focus on the relation between unemployment and city size, but similar endogeneity issues are experienced when regressing other variables of interest, such as unemployment fluctuations  $V(u_i)$  or the correlation between unemployment and wages ( $Corr(u_i, \omega_i)$ ).

<sup>13</sup>The simplest means of addressing the endogeneity issue at the local level is to rely on employment area fixed effects. However, we do not implement this strategy because it introduces additional problems. First, with employment area fixed effects, identification relies on time variations in local characteristics. Our data on local unemployment are available only since 2003. The variation of density over time is very limited in developed countries such as France. Therefore, short-term variations in density observed in such an estimate are likely to be generated by measurement errors. These noisy variations would likely produce biased estimates. Second, employment area fixed effects would not address the most important issue: reverse causality.

<sup>14</sup>Since the instruments are invariant over time, identification is in the cross-section. Thus, we average data on unemployment over 2003-2017 and data on wages over 2003-2013, and we run cross-sectional estimations.

(i.e., 1831) and another census from 1881, 50 years later.<sup>15 16</sup>

Our second set of instruments is composed of geological data. The geological data come from the European Soil Database, a raster with cells of 1 km by 1 km. The rationale behind these instruments is that geology and natural advantages (such as soil fertility) played a role in the emergence of cities. The idea that geology shapes human habitat has a long history in the social sciences. For instance, Siegfried (1913) shows that habitations are more agglomerated in limestone regions. At present, the role played by geology in agglomeration seems to have vanished. Indeed, due to the decreased role of agriculture in the national economy, these natural advantages are very unlikely to play a role in contemporary agglomeration. Specifically, we select 7 variables from the original European Soil Database. These variables include variables describing soil ruggedness (minimum elevation in the employment area), depth to rock, the water capacity of the subsoil (five categories), soil differentiation, geological characteristics (erodibility), the nature of the topsoil with respect to mineralogy (topsoil mineralogy), and the dominant parent material (six categories).

**Do history and geology have an impact on density?** The use of weak instruments may lead to larger biases than those produced by OLS. To assess the validity of our instrument, we regress local density on our instruments. Table 1 presents the partial correlations between instruments and our endogenous regressors. Columns (1) to (3) outline the partial correlations between our historical instruments and population density. We observe that these historical instruments are significantly and positively correlated with contemporary density. For readability, we do not report the coefficients of soil dummies, but at least one dummy is significant at 10 percent in each regression.

Stock and Yogo (2005) develop a test of weak instruments, which addresses the concern that weak instruments can lead to size distortions in the Wald tests of the parameters. For historical instruments, our F-test (joint significance of the instrument excluded from the structural model) values are over the critical value reported by Stock and Yogo (2005). This result confirms our first intuition: history is a strong instrument. Our results also reveal that some geological characteristics, such as soil ruggedness or depth to rock, have good explanatory power. However, as observed

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<sup>15</sup>For comparative purposes, we use the same set of instruments as in Combes et al. (2010), and we instrument for both the 1831 level of population and the growth between 1831 and 1881.

<sup>16</sup>This instrument suffers from the disadvantage that 35 employment areas in our sample had no urban population in 1831 (above 5,000 inhabitants). These areas include both rural areas and densely populated areas with strong municipal fragmentation, mainly in the Ile-de-France administrative region. To minimize weak instrument problems, we drop these thirty-five employment areas from our regression.

by Combes et al. (2010), the vast majority of geological instruments are weak.

To avoid the pitfall of weak instruments, we use instruments with an F-test value over the critical values tabulated by Stock and Yogo (2005), namely, the historical instruments, soil ruggedness, and depth to rock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(Population 1831)	0.419*** (0.082)		-0.246** (0.117)							
log(Population 1881)		0.468*** (0.047)	0.663*** (0.104)							
Ruggedness				-0.003*** (0.001)						
Depth to rock	No	No	No	No	Yes	No	No	No	No	No
Subsoil water capacity	No	No	No	No	No	Yes	No	No	No	No
Soil differentiation	No	No	No	No	No	No	Yes	No	No	No
Soil erodibility	No	No	No	No	No	No	No	Yes	No	No
Topsoil mineralogy	No	No	No	No	No	No	No	No	Yes	No
Parent material	No	No	No	No	No	No	No	No	No	Yes
Observations	277	277	277	277	277	277	277	277	277	277
R-squared	0.166	0.262	0.273	0.139	0.137	0.074	0.093	0.085	0.086	0.161
F-test (H0-all instrument are zero)	25.92	97.49	51.54	44.54	14.44	4.305	9.281	5.038	4.214	8.616

Note: Dependent variable: log (population density). Standard errors in parentheses; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$

**Table 1. FIRST-STAGE ESTIMATES**

**Are history and geology exogenous?** To be a good instrument, history and geology must affect actual unemployment only through their effect on density. To reduce endogeneity concerns, we select the earliest population estimates compiled by Guerin-Pace (1993). This census dates back to 1831. What drove the location of economic activities in the early 19<sup>th</sup> century is substantially different from what drives it at present. As detailed in Combes et al. (2010), French production structures have changed considerably over the last two centuries. The Industrial Revolution began late in France (compared to other regions in Europe, such as England or Wallonia). In 1831, France was mainly an agricultural country, and the primary sector employed approximately 60% of the workforce, while at present, the figure is only 5%. The 19<sup>th</sup> century witnessed the emergence of industry and its decline after the first oil boom. Spatial dependence on raw materials, such as coal, disappeared. Moreover, France experienced massive changes in its relations with its neighbors. In 1831, France was still recovering from the Napoleonic Wars, and thereafter, the country experienced a war with Prussia, in 1870, and the two world wars. The postwar years witnessed the emergence of European integration and the gradual erosion of the European Union's internal borders. The accumulation of structural changes and major historical events leads us to contend that history affects unemployment only through its effect on density and that past determinants of population agglomerations are orthogonal to current unemployment.

Geological variables compose our second set of instruments. As argued by Di Adario (2011), while people in the past settled in areas where the land was more fertile and water abundant, soil characteristics are not central to location choice at present (agricultural activities account for less than 5% of GDP at present). Moreover, geology has mostly been imposed by nature and does not result from human activity (Combes et al., 2010).

The exclusion restrictions may be violated if our instruments have a direct impact on the local social composition. Even if the historical urban population is used to instrument for current density, our estimation may be biased. Indeed, a city with a large population in the 19<sup>th</sup> century may supply a high level of amenities today through the presence of historical monuments. In this case, such historical amenities may influence the unemployment rate because of a spatial sorting of population (mobility across cities driven by amenities may determine the spatial distribution of the unemployment rate). However, our results are highly unlikely to be impacted by a violation of the exclusion restrictions since we test for the stability of our coefficient by switching between different instruments. Our instruments rely on different exclusion restrictions. Indeed, it seems very unlikely that a particular population

will move in conjunction with the presence of a certain type of geology (for instance, depth to rock) and as a consequence of the presence of historical amenities.

**Omitted variable bias.** It would be tempting to increase the strength of our regressions by including a set of control variables describing local economic characteristics. However, most control variables are plagued by the same endogeneity issue as density. These variables are likely bad controls (see Angrist and Pischke (2008)), and they should not be included in our regression models even when their inclusion might be expected to change the short regression coefficients. As explained by Combes et al. (2010), the drawback is that the exclusion restriction for the instruments (*i.e.*, lack of correlation between the instruments and the error) is more difficult to satisfy with a greater number of controls.<sup>17</sup>

## 4.2 The impact of city size on unemployment rate

Our theoretical model in Section 3 predicts that denser areas should experience higher unemployment rates. The results of our regressions are reported in Table 2. Our dependent variable is defined as the log of the average unemployment rate for the period 2003-2017 ( $\bar{u}_i = \sum_t u_{it}/T$ , where  $u_{it}$  is the quarterly unemployment rate prevailing in employment area  $i$  in time  $t$ , and  $T$  is the number of quarters). In Table 2, column (1) shows that denser areas experience higher unemployment: moving from an area in the first quartile of density to the last quartile increases unemployment by 6%.<sup>18</sup> For the sake of comparison between OLS and 2SLS, we limit our sample to employment areas with strictly positive urban populations in 1831. In columns (2)-(5), we perform the same regressions as in column (1), but we instrument population density. In column (2), we instrument the local level of density by historical instruments. Compared to their corresponding OLS coefficients, the 2SLS coefficients for the local level of density are substantially higher. In columns (3)-(5), we assess the strength of this finding by using different sets of instruments. The instruments are the soil ruggedness in column (3) and the depth to rock in column (4). The magnitude of our coefficients is stable across regressions, and the elasticity (which ranges between 0.12 and 0.15) implies that moving from an area in the first quartile of density to the last quartile increases unemployment by between 14% and

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<sup>17</sup>To assess the robustness of our results, we display in Appendix B the results obtained with a set of control variables. Our additional estimations show that our results are highly robust to the inclusion or exclusion of these controls.

<sup>18</sup>In our sample, we observe a factor of 3 for the inter-quartile of local density.

18%. Column (5) reports a regression that is useful to assess the exogeneity of our instruments because the instruments are of different natures<sup>19</sup>. In Table 2, we report the p-value of the Sargan-Hansen test of overidentification restrictions.<sup>20</sup> The high p-values of these statistics in column (5) confirms that the overidentification restriction is valid.

	(1)	(2)	(3)	(4)	(5)
	log of <i>average unemployment rate</i> [ $\log(u_i)$ ]				
	OLS	2SLS	2SLS	2SLS	2SLS
log(density)	0.057*** (0.016)	0.133*** (0.034)	0.155*** (0.035)	0.123** (0.055)	0.138*** (0.029)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-
F-test	-	51.54	44.54	14.44	74.3
P-value Hansen J statistic	-	0.63	-	0.08	0.57
Observations	277	277	277	277	277

This table reports the coefficients of OLS (1) and 2SLS (2-5) regressions of population density on the average local unemployment rate between 2003 and 2017. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 2.** IMPACT OF DENSITY ON UNEMPLOYMENT

### 4.3 The impact of city size on unemployment volatility

We now present and analyze the results associated with the impact of population density on unemployment volatility.

**Measuring unemployment volatility.** We first detail our methodology for measuring unemployment volatility. Variability refers to the extent to which the observed values of an economic variable deviate from the trend or reference value. Several alternatives are suggested in the literature for analyzing unemployment variability.

Many papers on economic volatility use a statistical filtering approach to isolate the cyclical and trend components. The standard deviation of the cycle is a

<sup>19</sup>As emphasized by Combes and Gobillon (2015), an exogeneity test using instruments of different natures is more meaningful. It is likely that historical and geological variables satisfy this property: even if geology initially influenced people’s location choices a very long time ago, many other factors have also determined the spatial distribution of the population. Therefore, the population size in the 19th century was not directly determined by local geology

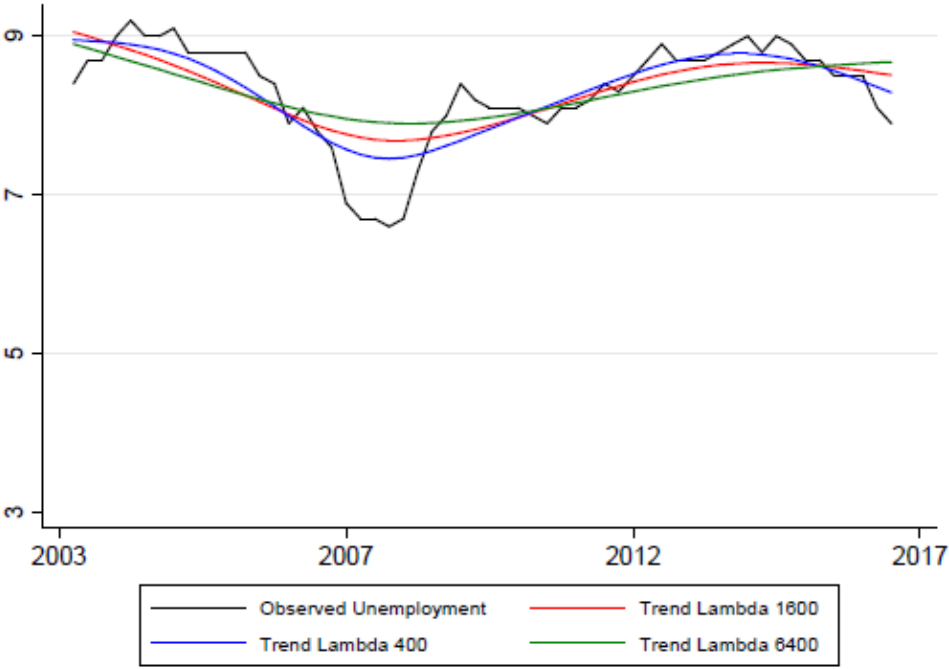
<sup>20</sup>We report the J statistic because this statistic is consistent in the presence of heteroskedasticity.



measure used to assess economic volatility. Filtering has the benefit of not imposing *a priori* any particular form on the behavior of the series (Cariolle and Goujon, 2015). In addition, filtering allows for a change in the trend component. As in Shimer (2005), who studies unemployment cycle frequency, we use the Hodrick and Prescott (1997) filter. Formally, cyclical decomposition is achieved by minimizing the following function:

$$\min_{\tau_{it}} \left( \sum_{t=1}^T (u_{it} - \tau_{it})^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{i,t+1} - \tau_{i,t}) - (\tau_{i,t} - \tau_{i,t-1})]^2 \right), \quad (18)$$

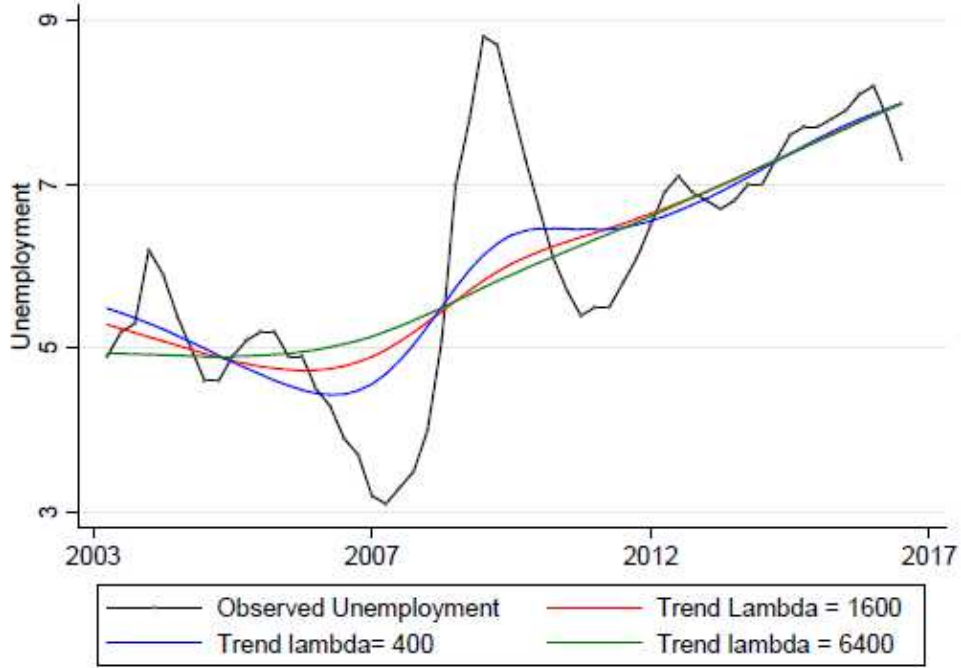
where  $\lambda > 0$  is a smoothing parameter. The choice of the value of  $\lambda$  is central and remains a subject of debate in the literature. For quarterly data, we use the widely accepted value of  $\lambda = 1600$  (Pedersen, 2001).<sup>21</sup>



**Figure 4.** Paris

Figures 4 and 5 display trends estimated for two employment areas with  $\lambda$  set at 1,600 and two extreme values ( $\lambda$  equal to 400 and 6,400). The Paris and Morteau employment areas (the latter being a small employment area) display very differ-

<sup>21</sup>We assess the robustness of our finding by testing the relation between density and unemployment volatility for two extreme values,  $\lambda = 400$  and  $\lambda = 6400$ . The results are reported in Appendix B.3



**Figure 5.** Morteau

ent patterns of unemployment variability. The long-term trend in unemployment in Paris is nearly constant between 2003 and 2017. Moreover, we note that cyclical fluctuations around the trend (*i.e.*, the gap between the observed unemployment value and the trend) are relatively muted in Paris. In contrast, long-term unemployment in Morteau grows between 2003 and 2017, and cyclical fluctuations around the trend are stronger in this small employment area.

For each employment area  $i$ , we compute  $V(u_i)$  as the deviation from the long-term trend:

$$V(u_i) = \sqrt{\sum_{t=1}^T \left( \frac{u_{it} - \hat{u}_{it}}{\hat{u}_{it}} \right)^2}, \quad (19)$$

where  $u_{it}$  is the observed quarterly unemployment rate in employment area  $i$  at time  $t$  and  $\hat{u}_{it}$  is the long-term trend of unemployment estimated by the Hodrick-Prescott filter approach.

**Impact of density on unemployment volatility.** In Table 3, we report the results obtained using the Hodrick-Prescott filter for  $\lambda = 1600$ . Table 3 shows that the unemployment rate is much more stable in dense areas. Column (1) reports our OLS

estimation. This estimation implies that moving from an area at the first quartile of density to one at the last quartile decreases our unemployment fluctuation index by approximately 6%. In columns (2)-(5), we instrument employment density. Compared to their corresponding OLS coefficients, the 2SLS coefficients for the local level of density are substantially higher in absolute value. Our IV estimations show that moving from an area in the first quartile of density to one in the last quartile translates into a decrease in our unemployment fluctuation index of approximately 25%. However, our coefficient is no longer significant in specification (4). Our instruments in column (4) are weak; therefore, we do not accord much weight to this particular result.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
log(density)	-0.053** (0.024)	-0.254*** (0.060)	-0.190** (0.098)	-0.064 (0.051)	-0.256*** (0.060)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
F-test	-	51.54	44.54	14.44	74.3
Hansen J statistic	-	0.01	-	0.3155	0.3665
Observations	277	277	277	277	277

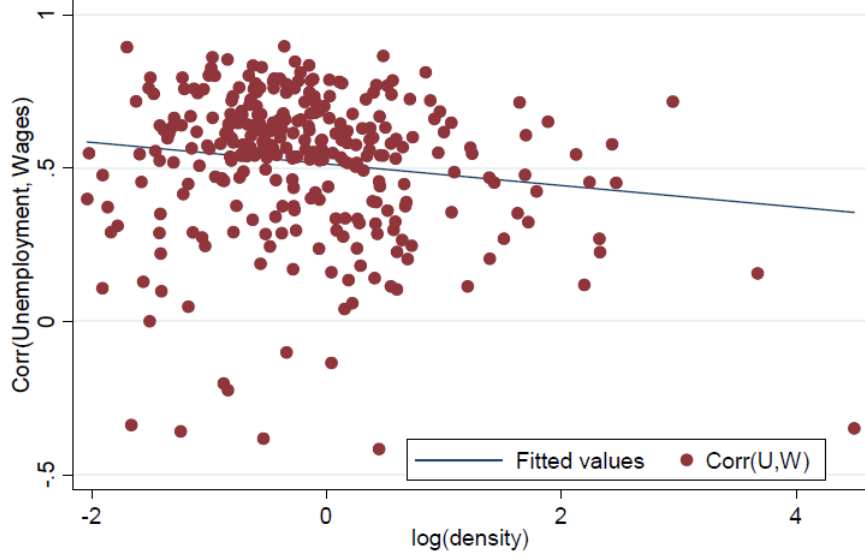
The table reports the coefficients of OLS regression in column (1) and 2SLS regressions in columns (2)-(5). The dependent variable is the log of unemployment rate volatility for the period 2003-2017. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 3.** UNEMPLOYMENT VOLATILITY AND CITY SIZE

#### 4.4 City size and the covariance between unemployment and wages

Our model predicts that more populated areas exhibit lower covariance between unemployment and wages. This is a key result of our model, which highlights the microeconomic foundations of job pooling as a source of agglomeration. To empirically test this mechanism, we exploit the *Déclarations Annuelles des Données Sociales* (DADS) for the period 2003-2013 that report annual earnings across workers for each employer. The DADS are collected by the French Institute for Statistics, and all employers must complete a report for each of their employees every year. From this database, we can compute the average wage rate every year for each employment area. For matching with wage data, we use annual data on local unemployment provided by the French Institute of Statistics over the period 2003-2013.

In Figure 6, we report a linear relation between city size and the correlation between the unemployment rate and wages. Note that instead of covariance, we pre-



**Figure 6.** City size and the simple correlation between wages and unemployment

fer to use the normalized version of the covariance, the correlation coefficient. As expected, Figure 6 reveals a positive correlation between wages and the unemployment rate. More interesting, this figure clearly displays a decreasing relationship between the correlation coefficient and density.

To more thoroughly assess this prediction, rather than regressing the simple correlation, we prefer to use the trend-filtered correlation to control for shocks common to all areas such as national business cycles. The idea is to focus our analysis on variations specific to each local labor market. This approach consists of regressing our variables of interest using a linear trend:

$$u_{iT} = \eta_0 + \eta_1 T + \epsilon_{iT}^u \quad (20)$$

$$\omega_{iT} = \zeta_0 + \zeta_1 T + \epsilon_{iT}^\omega \quad (21)$$

where  $u_{iT}$  is the annual unemployment rate,  $y_{iT}$  is the average annual wage  $\omega_{iT}$ , and  $T$  is a linear trend, while the parameters  $\eta_0$ ,  $\eta_1$ ,  $\zeta_0$ , and  $\zeta_1$  are the coefficients to be estimated. The variables  $\epsilon_{iT}^u$  and  $\epsilon_{iT}^\omega$  are the error terms associated with unemployment and wage equations. These error terms are the cycle component, and they correspond to the detrended unemployment rate and detrended wages, respectively. Hence, we can construct our measure of the trend-filtered correlation between unemployment and wages. As seen in Table 4, our regressions confirm that the correlation between wages and the unemployment rate decreases with city size.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	$Corr(w_i; u_i)$ 2SLS	2SLS	2SLS
log(density)	-0.075*** (0.029)	-0.131** (0.052)	-0.043 (0.073)	-0.136** (0.062)	-0.112** (0.045)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-
F-test	-	51.54	44.54	14.44	74.3
Hansen J statistic	-	0.24	-	0.01	0.22
Observations	277	277	277	277	277

The table reports the OLS regression coefficients in column (1) and 2SLS regression coefficients in columns (2)-(5). The dependent variable is the correlation between detrended wages and the detrended unemployment rate. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 4.** CITY SIZE AND CORRELATION BETWEEN DETRENDED UNEMPLOYMENT AND DETRENDED WAGES

#### 4.5 The impact of density on expected wage and wage fluctuations.

Even if the main predictions of our job pooling model are related to unemployment, our framework also has predictions on expected wages and wage fluctuations. Hence, we can explore the relevance of the proposed channel of job pooling by displaying two additional tests linking wages and city size.

We first check whether the average local wage over the period 2003-2013 is higher in more densely populated areas. Our dependent variable is defined as the log of the average wage over the period 2003-2013 ( $\bar{w}_i = \sum_t w_{iT}/T$ , where  $w_{iT}$  is the average annual salary prevailing in employment area  $i$  and  $T$  is the number of years).<sup>22</sup> We regress the log of the average local wage on the log of the local density. Table 5 confirms a well-known relationship between agglomeration and wages. The measured density elasticity of the mean wage is 0.05, which is very close to previous results in the literature (Ciccone, 2002) or (Combes et al., 2010). In columns (2)-(5), we perform the same regressions as in column (1), but we instrument population density. The magnitude of our coefficients is rather stable across regressions, at expected for column (3), where local density is instrumented by the depth to rock. When city size is instrumented by depth to rock, the measured density elasticity of mean wage is at 0.025, which is half that of previous estimates. We need to bear in mind that our geological instruments are at the limit of being considered a weak instrument. In our different regressions, elasticity ranges between 0.025 and 0.057, implying that when

<sup>22</sup>Our model predicts the equalization of expected incomes across cities. Nevertheless, our theory abstracts from urban costs (e.g., congestion, local pollution, housing prices). If we consider urban costs in our model, we can obtain an interior solution where expected income is higher in larger cities, as urban costs increase with city size.

density is twice as high, wages are between 1.7 and 4% higher.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	log( $W_i$ ) 2SLS	2SLS	2SLS
log(density)	0.057*** (0.005)	0.061*** (0.008)	0.025*** (0.009)	0.055*** (0.009)	0.050*** (0.007)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-
F-test	-	51.54	44.54	14.44	74.3
Hansen J statistic	-	0.36	-	0.08	0.0
Observations	277	277	277	277	277

The table reports the OLS regression coefficients in column (1) and 2SLS regression coefficients in columns (2)-(5). The dependent variable is the log of the average wage for the period 2003-2013. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 5. WAGES AND CITY SIZE**

These results confirm a well-established result in urban economics: a positive relation between urban density and wages. However, different labor market mechanisms suggested by urban economic theory can explain this result (e.g., spatial externality, matching, sorting, labor pooling). To better assess the relevance of the job pooling channel, we explore the relationship between wage volatility and urban density. According to our framework, labor income fluctuations are expected to be lower in larger cities. To the best of our knowledge, our paper is the first to consider wage fluctuations across space.

Wage volatility is computed using a similar procedure to that used to examine unemployment volatility (the Hodrick-Prescott Filter). Between 2003 and 2009, for each employment area  $i$ , we compute  $V(w_i)$  as the deviation from the long-term trend of wages estimated by the Hodrick-Prescott filter approach. For annual data, we use the value of  $\lambda = 150$ .<sup>23</sup> In columns (2)-(5), we instrument employment density following the same procedure as detailed above. We observe in columns (3) and (4) that the impact of local density is no longer significant. Again, our geological instruments are weak, and we do not accord much weight to the results in this case<sup>24</sup>. Our estimations indicate that when density is twice as high, wage volatility is

<sup>23</sup>We assess the robustness of our finding by testing the relation between density and unemployment volatility for two extreme values,  $\lambda = 100$  and  $\lambda = 200$ . The results are available upon request.

<sup>24</sup>Another plausible explanation is that IV estimation recovers a local average treatment effect, which is the average effect of the treatment for the subpopulation whose behavior was influenced by the instrument (Baum-Snow and Ferreira, 2015). It is plausible that density does not influence wage volatility for the particular populations of cities that are densely populated due to “good” geological conditions. Nevertheless, the results obtained with other sets of instruments remain fully valid

between 11% and 30% lower.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
log(density)	-0.170*** (0.059)	-0.536*** (0.175)	-0.033 (0.139)	0.412 (0.253)	-0.375*** (0.132)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-
F-test	-	51.54	44.54	14.44	74.3
Hansen J statistic	-	0.01	-	0.34	0.0
Observations	277	277	277	277	277

The table reports the OLS regression coefficients in column (1) and 2SLS regression coefficients in columns (2)-(5). The dependent variable is the log of wage volatility for the period 2003-2009. Wage volatility is computed using a Hodrick-Prescott Filter with  $\lambda = 150$ . The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 6.** WAGE VOLATILITY AND CITY SIZE

## Conclusion

In this article, we focus on a topic that is understudied in the academic literature: the impact of city size on unemployment. This question is of crucial importance in the European context, where regional unemployment disparities remain high.

To explore this issue, we propose a model of job pooling with an imperfect labor market in which risk-neutral agents make decisions under uncertainty. We relax the hypothesis of competitive wage setting that is usually made in labor pooling models, and we allow for non-competitive wages and unemployment. To the best of our knowledge, we are the first study to include unemployment in a model of agglomeration with risk sharing and to analyze how job pooling and job competition shape equilibrium unemployment and its variability. In our setting, labor unions and firms bargain locally over wage rates. Involuntary unemployment arises in equilibrium. The bargaining process between firms and unions is affected by firm-specific shocks. We show that a larger city size increases the unemployment rate but reduces its volatility. The probability of being unemployed is less sensitive to idiosyncratic shocks in highly populous cities.

We exploit French unemployment data from between 2003 and 2017 at the employment area level to empirically test our main predictions. As expected, a higher urban density raises local unemployment, whereas it reduces unemployment rate fluctuations. We also investigate the mechanism driving the job pooling effect. Our

regression shows that the covariance between wages and unemployment probability decreases with city size. Our regressions address the issue of endogeneity due to reverse causality or to missing variables affecting both local density and unemployment. We implement an instrumental variable strategy, using history and geology as sources of exogenous variation in local density. Our estimates are very robust to a change in the sets of instruments used, showing that our results are not too local and that the exclusion restrictions are very unlikely to be violated.

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## Appendix A. Theory

### A.1. Efficient bargaining model

We consider the general case in which  $\theta > 0$  and show that our conclusion is robust to a change in how the wage rate ( $\omega_i$ ) and the quantity of labor hired ( $\ell_i$ ) are determined. In line with McDonald and Solow (1981), we assume that firms and unions simultaneously bargain over wages and employment. The profit of each firm is given by  $\pi_i(\ell) = q(\ell) - \omega\ell$ . Recall that when the unions and firms bargain over wages and employment, the Nash product is

$$\mathcal{N} = \pi_i^{\gamma_i} \left[ \ell_i^{\theta_i} (\omega_i - \bar{\omega})^{1-\theta_i} \right]^{1-\gamma_i}. \quad (22)$$

The first-order condition implies that  $\partial\mathcal{N}/\partial\ell_i = 0$  and  $\partial\mathcal{N}/\partial\omega_i = 0$ , and thus,

$$\ell_i = \frac{2[\gamma_i(1 - \theta_i) + \theta_i]}{1 + \gamma_i} (\alpha - \bar{\omega}), \quad (23)$$

and

$$\omega_i = \alpha - \frac{\gamma_i(2 - \theta_i) + \theta_i}{1 + \gamma_i} (\alpha - \bar{\omega}). \quad (24)$$

We return to the case discussed in Section 3 when  $\theta_i = 0$ . The covariance between the probability of unemployment and firm-specific wage bargaining shocks (through  $\gamma_i$  or  $\theta_i$ ) is still negative and decreases in the size of the labor force.

### A.2. Plateau of equilibria

For simplicity, we assume that  $\zeta_n = \zeta_\ell = 1$ . Hence,  $\varphi = 1/(1 + n/L)$ . Following the approach developed by Ellison and Fudenberg (2003), the expected income and the expected profit can be rewritten as follows:  $y^\ell = F_\ell - G_\ell/L$  with  $F_\ell \equiv (\alpha - \varphi\tilde{\alpha})(1 - \varphi)\tilde{\alpha}$  and  $G_\ell \equiv \tilde{\alpha}^2\mathbb{V}(\epsilon)$  and  $\mathbb{E}(\pi) = F_n - G_n/L$  with  $F_n \equiv \frac{\tilde{\alpha}^2}{2}[\varphi^2 + \mathbb{V}(\epsilon)]$  and  $G_n = 0$ . It follows that  $F_\ell$  (resp.,  $F_n$ ) increases (resp., decreases) with the firm-to-worker ratio ( $n/L$ ). Hence, according to Theorem 1 in Ellison and Fudenberg (2003), there exists a plateau of equilibria with two “active” cities. Since  $G_\ell > 0$  and  $G_n = 0$ , the width of the plateau is determined by the workers’ incentive constraint. Applying Theorem

1, we find that  $\frac{n_A}{n_T} = \frac{L_A}{L_T} \in \{r; 1 - r\}$  with

$$r \equiv \frac{\mathbb{V}(\epsilon)}{2\mathbb{V}(\epsilon) + (1 - \varphi_T)\varphi_T \left( \frac{1+\alpha}{\bar{\alpha}} - 2\varphi_T \right)} \quad (25)$$

with  $\varphi_T \equiv 1/(1 + n_T/L_T)$ . The size of this plateau decreases with the variance of shocks. In other words, higher uncertainty makes agglomeration more likely.

## Appendix B. Controlling for covariates

In this appendix, we report several other possible determinants of local unemployment. Elhorst (2003) offer the most widely cited literature review on this topic, providing a list of the commonly employed explanatory variables. These variables are the natural growth of the labor force, migration patterns, wages, employment growth, the industrial mix, the educational attainment of the population, and the local social environment, such as the degree of unionization. Given the low number of observations, we cannot be exhaustive and include all these controls at a detailed level. Moreover, we do not control for variables linked to the pooling mechanism described in section 3, namely, the natural growth of the labor force, migration patterns, wages, employment growth or the local degree of unionization.

We control for the industrial mix by including the sector composition estimated by the French National Institute of Statistics. It is often argued that one of the main causes of regional unemployment disparities is the location of declining or growing industries in particular regions Elhorst (2003). We compute the local share for each industry using the international industry classification at the so-called A10 level. We also control for the educational attainment of the population by computing, for each employment area, the shares of the total population without a diploma, with vocational diplomas, and with a high school degree. Because the educational attainment of the population is very aggregated, we also control for socioeconomic composition to control for differences in socioeconomic composition.<sup>25</sup>

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<sup>25</sup>We use data from the national census. The French National Institute of Statistics offers a classification of professions and PCS. This classification categorizes individuals according to their professional situation, taking into account several criteria: their profession, economic activity, qualification, hierarchical position and status. For each employment zone, we compute the shares of the population classified as craftpersons, employees, blue collar workers, or executives.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	$\log(\bar{u}_i)$ 2SLS	2SLS	2SLS
log(density)	0.087*** (0.017)	0.454*** (0.104)	0.109** (0.051)	0.063 (0.067)	0.266*** (0.055)
Agriculture	-1.798 (1.457)	-1.000 (1.954)	-1.751 (1.407)	-1.850 (1.433)	-1.408 (1.494)
Manufacturing	-0.369 (1.389)	-2.124 (1.840)	-0.472 (1.324)	-0.253 (1.405)	-1.226 (1.420)
Construction	-2.527 (1.672)	-4.375 (2.765)	-2.636 (1.627)	-2.405 (1.657)	-3.430* (2.013)
Trade	0.279 (1.382)	-4.523** (2.188)	-0.003 (1.386)	0.596 (1.652)	-2.067 (1.540)
Communication	1.836 (2.183)	-2.968 (3.208)	1.555 (2.196)	2.153 (2.251)	-0.510 (2.458)
Financial	-0.547 (1.604)	-2.949 (2.412)	-0.688 (1.553)	-0.389 (1.643)	-1.720 (1.727)
Real estate	0.845 (4.180)	-16.375** (6.949)	-0.164 (4.388)	1.982 (5.012)	-7.566 (4.652)
Specialized activities	4.044** (1.718)	-0.977 (2.459)	3.750** (1.794)	4.376** (1.914)	1.591 (1.875)
Public administration	2.219 (1.484)	-0.169 (1.916)	2.079 (1.437)	2.377 (1.529)	1.052 (1.522)
Without any diploma	2.805*** (0.635)	2.271** (0.953)	2.774*** (0.624)	2.840*** (0.627)	2.544*** (0.703)
Vocational diploma	0.840 (0.892)	0.577 (1.403)	0.825 (0.876)	0.857 (0.864)	0.712 (1.037)
High school	-0.055 (1.560)	1.536 (2.279)	0.038 (1.473)	-0.160 (1.554)	0.722 (1.679)
Craftwork	5.331*** (1.097)	9.376*** (2.043)	5.568*** (1.144)	5.064*** (1.245)	7.306*** (1.371)
White Collar	-0.841 (1.248)	-1.586 (1.546)	-0.885 (1.209)	-0.792 (1.244)	-1.205 (1.252)
Employee	0.364 (1.126)	3.082* (1.855)	0.523 (1.139)	0.185 (1.244)	1.692 (1.317)
Blue Collar	0.525 (0.700)	1.219 (1.096)	0.566 (0.668)	0.479 (0.693)	0.864 (0.787)
Historical Instruments	-	√	-	-	√
Ruggedness	-	-	√	-	√
Depth to Rock	-	-	-	√	-
F-test	-	18.1	25.4	14.5	22.6
Hansen J statistics	-	0.16	-	0.39	0.0
Observations	277	277	277	277	277

**Table 7.** Unemployment and city size when covariates are included

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
	log( $V(u_i)$ ) [ $\lambda = 1600$ ]				
log(density)	-0.113*** (0.037)	-0.591*** (0.162)	-0.150 (0.144)	-0.232* (0.130)	-0.398*** (0.131)
Agriculture	-1.315 (3.395)	-2.355 (3.431)	-1.397 (3.261)	-1.576 (3.211)	-1.937 (3.227)
Manufacturing	-0.265 (3.462)	2.022 (3.460)	-0.086 (3.383)	0.307 (3.314)	1.102 (3.272)
Construction	2.281 (3.458)	4.688 (4.065)	2.469 (3.374)	2.884 (3.367)	3.721 (3.571)
Trade	-1.536 (3.400)	4.721 (3.976)	-1.046 (3.743)	0.031 (3.561)	2.206 (3.601)
Communication	-2.868 (5.647)	3.392 (5.661)	-2.378 (5.558)	-1.301 (5.602)	0.875 (5.351)
Financial	-0.422 (4.115)	2.708 (4.539)	-0.176 (4.090)	0.362 (4.009)	1.450 (4.079)
Real estate	-0.361 (9.258)	22.078* (11.942)	1.397 (11.381)	5.258 (10.420)	13.057 (10.966)
Specialized activities	-6.864* (3.795)	-0.321 (4.152)	-6.352 (4.015)	-5.226 (3.953)	-2.952 (3.759)
Public administration	-4.362 (3.485)	-1.250 (3.495)	-4.118 (3.494)	-3.583 (3.342)	-2.501 (3.348)
Without any diploma	-0.567 (1.414)	0.129 (1.611)	-0.513 (1.355)	-0.393 (1.380)	-0.151 (1.417)
Vocational diploma	3.349* (1.864)	3.691 (2.306)	3.376* (1.812)	3.434* (1.852)	3.553* (2.008)
High school	1.510 (3.052)	-0.563 (3.879)	1.348 (3.052)	0.991 (3.047)	0.270 (3.421)
Craftwork	-3.355 (2.123)	-8.626*** (3.249)	-3.768 (2.358)	-4.675* (2.550)	-6.507** (2.687)
White Collar	7.431*** (2.497)	8.400*** (2.650)	7.507*** (2.428)	7.674*** (2.371)	8.011*** (2.437)
Employee	1.328 (2.122)	-2.213 (2.943)	1.051 (2.361)	0.441 (2.278)	-0.790 (2.583)
Blue Collar	2.987** (1.356)	2.082 (1.646)	2.916** (1.310)	2.760** (1.341)	2.445* (1.426)
Historical Instruments	-	√	-	-	√
Ruggedness	-	-	√	-	√
Depth to Rock	-	-	-	√	-
F-test	-	18.1	25.4	14.5	22.6
Hansen J statistic	-	0.0	-	0.37	0.0
Observations	277	277	277	277	277

**Table 8.** Unemployment volatility and city size when covariates are included

## Appendix B.1: Attempt to tackle the endogeneity of covariates

However, as underlined in section 4.1, most control variables are likely plagued by the same endogeneity issue as density. In other words, they are bad controls (Angrist and Pischke, 2008) because they are themselves outcome variables of the local level of unemployment. We implement further estimations in which some control variables are also instrumented. As suggested by Angrist and Pischke (2008), we use lagged control variables as instruments. The rationale behind this strategy is that predetermined variables are generally good controls because they cannot themselves be outcomes in the causal nexus. In Table 9, the current levels of educational and occupational compositions are instrumented with the level of educational and occupational compositions observed in 1968, the oldest national census available.<sup>26</sup> The results are reported in Table 9 and show that our results hold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		log( $\bar{u}_i$ )				log( $V(u_i)$ ) [ $\lambda = 1600$ ]		
log(density)	0.497*** (0.128)	0.195*** (0.048)	0.209*** (0.056)	0.248*** (0.047)	-0.642*** (0.189)	-0.232** (0.091)	-0.237** (0.095)	-0.323*** (0.094)
Without any diploma	0.058 (6.990)	2.155 (1.441)	2.348 (1.444)	1.464 (1.474)	14.330 (11.551)	0.261 (2.222)	0.137 (2.181)	1.458 (2.394)
Vocational diploma	-6.369 (8.749)	-0.073 (2.033)	0.234 (2.031)	-1.543 (1.987)	27.379* (14.043)	4.764 (3.327)	4.557 (3.272)	7.311** (3.387)
High school	-13.916 (9.840)	-0.251 (2.236)	-0.184 (2.259)	-1.726 (2.343)	29.993** (15.047)	3.613 (3.969)	3.382 (3.920)	6.168 (4.059)
Craftwork	6.841 (5.815)	6.876** (2.821)	7.763*** (2.825)	4.907* (2.900)	-7.698 (8.071)	-7.003 (4.593)	-7.004 (4.713)	-3.591 (4.709)
White Collar	-1.270 (5.878)	2.506 (2.987)	2.850 (3.052)	-0.915 (2.645)	15.787** (7.537)	6.709 (4.538)	6.795 (4.422)	12.636*** (4.212)
Employee	14.873** (6.313)	7.233** (2.855)	7.342** (2.977)	9.076*** (3.040)	-19.882** (9.328)	-6.720 (4.731)	-6.081 (4.535)	-9.913* (5.114)
Blue Collar	-2.482 (7.654)	1.267 (2.432)	0.984 (2.352)	-0.411 (2.603)	-2.713 (13.395)	4.699 (4.722)	4.687 (4.487)	7.606 (4.972)
Observations	277	277	277	277	277	277	277	277
Educational composition in 1968	✓	✓	✓	✓	✓	✓	✓	✓
Occupational composition in 1968	✓	✓	✓	✓	✓	✓	✓	✓
Historical Instruments	✓	-	-	✓	✓	-	-	✓
Ruggedness	-	✓	-	✓	-	✓	-	✓
Depth to Rock	-	-	✓	-	-	-	✓	-

Columns (1)-(4) report the 2SLS estimates of the impact of local density on the level of unemployment. Columns (5)-(8) report the 2SLS estimates of the impact of local density on unemployment volatility. Educational and occupational compositions are instrumented by past educational and occupational compositions. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant and sectoral composition. Standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 9.** TACKLING THE ENDOGENEITY OF CONTROL VARIABLES

<sup>26</sup>We cannot instrument for the local industrial mix because past data on industrial composition are not publicly available.



## Appendix B.2: Controlling for the economic mobility within employment areas.

More interestingly, we control for mobility across sectors or occupations within employment areas by constructing two indices. Both indices are independent of the local workforce size.

The first (the sectoral index) assesses the ability to move across industries in a particular local labor market. We measure the extent to which employment areas use similar types of labor by first constructing a matrix at the national level that includes, for each industry, the likelihood of retraining in another industry.<sup>27</sup> This national matrix leads us to track movement across industries and to obtain a measure of labor pooling that is less dependent on industry classification. We then combine this national matrix of movement with the local population distribution across industries.

The second index is similar to the first, but it measures mobility between occupations rather than between industries. We first construct a matrix at the national level that includes, for each occupation, the likelihood of retraining in another occupation.<sup>28</sup> Then, we combine this national matrix with the local population distribution across occupations.

Both indices are a way of measuring the heterogeneity of local labor markets. Our indices reduce heterogeneity to one dimension, which will otherwise be measured by controlling for the local share of each industry and category. Therefore, we cannot directly interpret the sign of our indices; this approach is rather a way of offsetting labor market composition heterogeneity.

We regress unemployment (table 10) and unemployment variability (table 11) on density while controlling for workforce composition.<sup>29</sup> In Table 10, our coefficients of interest remain nearly unchanged when we control for workforce similarity is controlled. The coefficients associated with our indices are not significantly different from zero. In Table 10, our coefficients of interest remain nearly unchanged after controlling for workforce similarity. The only notable exception concerns specification (4), where density is instrumented by soil ruggedness. The coefficients associated

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<sup>27</sup>We use the most detailed level available, namely, A64.

<sup>28</sup>The classification is detailed into 29 occupations.

<sup>29</sup>We do not include other controls in our regression because they are likely to be collinear to our indices. Indeed, our indices can be interpreted as a way to measure local labor heterogeneity in terms of industrial mix and socio-demographic composition. Our indices are a way to reduce heterogeneity to one dimension, which will otherwise be measured by controlling for the local share of each industry and category.

with density are no longer significantly different from zero. This result is expected because we introduce a number of “bad controls” into our specification.

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	$\log(\bar{u}_i)$ 2SLS	2SLS	2SLS
log(density)	0.046** (0.019)	0.163*** (0.058)	0.159*** (0.039)	0.092* (0.053)	0.159*** (0.040)
Sectoral Index	-0.117 (0.098)	0.226 (0.195)	0.213 (0.152)	0.019 (0.186)	0.213 (0.152)
Socio-demographic Index	0.018 (0.218)	0.021 (0.279)	0.021 (0.275)	0.019 (0.235)	0.021 (0.276)
Historical Instruments	-	√	-	-	√
Ruggedness	-	-	√	-	√
Depth to Rock	-	-	-	√	-
F-test	-	20.5	34.8	23.0	36.7
Hansen J statistic	-	0.0	-	0.27	0.0
Observations	277	277	277	277	277

Column (1) reports the OLS estimates of the impact of local density on the level of unemployment. Columns (2)-(4) report the 2SLS estimates of the impact of local density on the level of unemployment. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 10.** UNEMPLOYMENT AND WORKFORCE HOMOGENEITY

	(1)	(2)	(3)	(4)	(5)
	OLS	log( $V(u_i)$ ) [ $\lambda = 1600$ ]			2SLS
		2SLS	2SLS	2SLS	2SLS
log(density)	-0.084*** (0.032)	-0.386*** (0.096)	-0.162* (0.095)	-0.100 (0.061)	-0.293*** (0.076)
Sectoral Index	-0.428** (0.195)	-1.309*** (0.371)	-0.656* (0.341)	-0.475* (0.248)	-1.038*** (0.312)
Socio-demographic Index	1.097*** (0.398)	1.090** (0.495)	1.095*** (0.399)	1.097*** (0.394)	1.092** (0.442)
Historical Instruments	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-
F-test	-	20.5	34.8	23.0	36.7
Hansen J statistic	-	0.0	-	0.27	0.0
Observations	277	277	277	277	277

Column (1) reports the OLS estimates of the impact of local density on the unemployment volatility. Columns (2)-(4) report the 2SLS estimates of the impact of local density on unemployment volatility. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 11. UNEMPLOYMENT VOLATILITY AND WORKFORCE HOMOGENEITY**

### Appendix B.3: Using alternative measures of volatility

In Table 12, we assess the robustness of our findings by testing the relation between density and unemployment volatility for two extreme values of  $\lambda$  (*i.e.*,  $\lambda = 400$  and  $\lambda = 6400$ ). Our results appear highly robust, as density has a strong and negative impact on unemployment volatility for all specifications except specification (8), which is very likely to be plagued by weak instrument bias.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	log( $V(u_i)$ ) [ $\lambda = 400$ ]			2SLS	OLS	log( $V(u_i)$ ) [ $\lambda = 6400$ ]			2SLS
		2SLS	2SLS	2SLS	2SLS		2SLS	2SLS	2SLS	2SLS
log(density)	-0.062** (0.025)	-0.276*** (0.063)	-0.223** (0.108)	-0.085* (0.050)	-0.281*** (0.063)	-0.053** (0.024)	-0.254*** (0.060)	-0.190* (0.098)	-0.064 (0.051)	-0.256*** (0.060)
Historical Instruments	-	✓	-	-	✓	-	✓	-	-	✓
Ruggedness	-	-	✓	-	✓	-	-	✓	-	✓
Depth to Rock	-	-	-	✓	-	-	-	-	✓	-
F-test	-	51.54	44.54	14.44	74.3	-	51.54	44.54	14.44	74.3
Hansen J statistic	-	0.01	-	0.64	0.47	-	0.01	-	0.3155	0.3665
Observations	277	277	277	277	277	277	277	277	277	277

Columns (1)-(5) report the results when the volatility of the unemployment rate is estimated with  $\lambda = 400$ , and columns (6)-(10) report the results when the volatility of the unemployment rate is estimated with  $\lambda = 6400$ . The table reports the OLS regression coefficients in column (1) and the 2SLS regression coefficients in columns (2)-(5). The dependent variable is the log of unemployment rate volatility for the period 2003-2017. The sample is restricted to employment areas with non-null urban population in 1831. All regressions include a constant. Robust standard errors are in brackets; \* =  $p < 0.10$ , \*\* =  $p < 0.05$ , and \*\*\* =  $p < 0.01$ .

**Table 12. UNEMPLOYMENT VOLATILITY WITH  $\lambda = 400$  AND  $\lambda = 6400$**