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JEL Classification: R10, R12, R32

Keywords: Agglomeration economies, Firm-level labor share, Firms location decisions

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Does the urban wage premium imply higher firm-level labor shares in cities?*

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January 15, 2024

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1 Introduction

Individual wages are higher in denser and/or bigger cities.[1] This is not only the consequence of the spatial sorting of heterogeneous firms and workers across local labor markets. It also reflects agglomeration economies, i.e. the positive externalities at play between them.[2] Does the urban wage premium imply that firms distribute a higher share of their value added to workers in big cities? The question has been largely overlooked so far. Sill, how factor shares vary with local employment density may have important implications for the location decisions of firms. I try here to fill this gap.

I find that on average, the firm-level labor share increases with local employment density, but this relationship is highly heterogeneous across industries. Through the lens of a theoretical framework featuring a CES production function, I show that this heterogeneity arises because both the density-elasticity of the relative cost of labor (adjusted for productivity) and the elasticity of substitution between capital and labor vary across industries. The magnitude of the effects I find in the data implies that in industries where the density-elasticity of the firm-level labor share is non-null, agglomeration economies are capital-biased. I also find in the data that all else equal, industries where the labor share increases with density are less likely to locate in denser areas.

I develop the analysis in three steps. First, I use French firm-level data to estimate the elasticity of the firm-level labor share to local employment density. As for the relationship between individual wages and local density, several omitted firm-level and local characteristics make the estimation of this elasticity challenging. In particular, bigger and more productive firms, which are disproportionately found in denser places, generally have higher market power on the output market (higher markups), and thus a lower labor share. Also, denser labor markets tend to be more competitive which could drive up wages, and the firm-level labor shares too. Workers in denser labor markets are on average more educated and more productive, which may affect their bargaining power and the labor share of the firms employing them. Finally, firms with specific factor-biased productivity parameters may sort into denser places, or some unobserved characteristics of bigger cities may have factor-biased productivity-enhancing effects (quality of public infrastructure for example). I address these endogeneity concerns by including relevant controls, and by relying on an IV strategy where local urban population density in the 19^{th} century is used as an instrument for current employment density. I find that the density-elasticity of the firm-level labor share is highly heterogeneous across the 3-digit manufacturing industries in my sample. The firm-level labor share increases with density in 29 industries out of 91 (33% of the workforce of these 89 industries), it remains unchanged in 50 of them (50% of the workforce), and it decreases in the remaining 11 industries (17% of the workforce).

To give a structural interpretation to these patterns, I propose a theoretical framework

[1]Employment density and city size are strongly positively correlated in the data.

[2]For a review of the theoretical mechanisms underlying these externalities, see Duranton and Puga (2004) and Behrens and Robert-Nicoud (2015), and for a review of the estimation of agglomeration economies, see Rosenthal and Strange (2004), Combes and Gobillon (2015) and Ahlfeldt and Pietrostefani (2019).

where firm-level value-added depends on capital and labor following a CES production function. Note that the paper is focused on how the local surplus of income attributable to agglomeration economies is shared between labor and capital. I thus use a value added production function and ignore materials. I show that the elasticity of the firm-level labor share to local employment density depends on two parameters: i) the density-elasticity of the relative returns to production factors adjusted for their factor-augmenting productivity;[3] ii) the elasticity of substitution between labor and capital within the firm. Most papers estimating the effect of local economic density on individual wages assume the production function is Cobb-Douglas (Combes and Gobillon, 2015). Under this assumption, when the relative cost of production factors varies, firms adjust their factor mix by the same proportion. The impact of local density on the firm-level factor share is then necessarily null. The question becomes non-trivial when agglomeration economies affect the relative returns to production factors *and* when the elasticity of substitution between capital and labor is not equal to one. Building on recent advances on the estimation of CES production functions, I estimate the elasticity of substitution between capital and labor separately for the three broad categories of industries identified in the first step. In all three categories, it significantly differs from one. Based on these estimates and on my conceptual framework, for each broad sector, I structurally infer the average density-elasticity of the productivity-adjusted relative cost of production factors. The magnitude of the elasticities I find implies that the relative cost of labor increases with density in industries where the density-elasticity of the firm-level labor share is non null. Moreover, in these industries, my empirical results imply that agglomeration economies are more capital- than labor-augmenting.

In the last part of the paper, I discuss the implications of my results for the location decisions of firms. From a theoretical perspective, firms are assumed to locate where their expected profit is the highest. Denser places are more attractive to firms because of the externalities and the higher market access they offer. On the other hand, production factors, especially labor, are generally more expensive in big cities, which acts as a dispersion force for some firms. This is why theoretically, sectors that are less sensitive to agglomeration economies and more labor-intensive should be less likely to locate in denser places. My findings further imply that all else equal, high-density places should be less attractive to industries where firms cannot easily adjust their factor mix. I estimate count models and show exactly that: firms in industries where the labor share increases with density are less likely to locate in denser areas, while the opposite is true for firms in industries where the labor share decreases with density. This holds controlling for several other determinants of firms' location decisions (including the sectoral average labor share and the sensitivity to agglomeration economies). This effect is quantitatively important. For a manufacturing firm, belonging to an industry in which the firm-level labor share increases with density is equivalent to a 1.38 standard-deviation increase in its sectoral average labor intensity. On the opposite, belonging to an industry in which the firm-level labor share decreases with density is equivalent to a 2.68 standard-deviation

[3] For the sake of concision, in the rest of the paper, I will often simply use "relative returns" (or "relative cost") for "relative returns adjusted for factor-augmenting productivity".

decrease in its sectoral average labor intensity

This paper makes several contributions. First, it obviously relates to the literature on the estimation of agglomeration economies. The modern approach started by Ciccone and Hall (1996) counts number of studies on the US (Glaeser and Mare, 2001; Henderson, 2003; Greenstone et al., 2010), France (Combes et al., 2008, 2010; Martin et al., 2011), Spain (Roca and Puga, 2017), Italy (Di Addario and Patacchini, 2008; Mion and Naticchioni, 2009), Canada (Baum-Snow et al., 2020) and other countries. Be it with worker-level wages, firm-level TFP or firm-level sales, these papers assess the magnitude of agglomeration economies by regressing measures of individual productivity on various proxies for agglomeration economies. Here, I do not seek to estimate the magnitude of agglomeration economies but I am interested in how they affect the mix of production factors at the firm-level. This relates to older papers discussing whether agglomeration economies are Hicks-neutral or factor-augmenting (Henderson, 1986; Tabuchi, 1986; Calem and Carlino, 1991). They could not reach a clear-cut conclusion so that Hicksian neutrality became the standard assumption (Glaeser et al., 1992; Henderson et al., 1995). However, these papers used semi-aggregated (city-level) data and faced well-known endogeneity issues that are inherent to the estimation of agglomeration economies. There were also conceptual issues since the aggregate production function at the city-level might differ from the micro production functions that govern the activity of the firms located in that city (see Houthakker, 1955). I revisit this older literature using firm-level data and show that agglomeration economies do have productivity-enhancing effects that are not Hicks-neutral.[4]

I also participate in the recent literature on the determinants of the firm-level labor share. Firm-level market power on the output market (see, e.g., De Loecker et al., 2020; Autor et al., 2020; Kehrig and Vincent, 2021) and on the labor market (see Manning, 2021, for a review), as well as technological change (see, e.g., Acemoglu and Restrepo, 2018; Oberfield and Raval, 2021) and international trade (see, e.g., Mertens, 2020; Panon, 2020) have been emphasized as potential drivers of the decline in the aggregate labor share observed in many countries over the past decades (Elsby et al., 2013; Karabarbounis and Neiman, 2014). The perspective here is very different here. I am interested in how geography shapes differences in the factor mix of firms in a given year and industry, not in the evolution of the aggregate labor share over time.

Finally, I contribute to the literature on the spatial sorting of firms and industries. The average labor intensity of the production function and the sensitivity to agglomeration economies have already been emphasized as important drivers of firms' location decisions (see, among others, Combes et al., 2012; Gaubert, 2018). I show that how firms adjust their factor shares to local density is another important dimension along which industries sort across locations.

[4] To do so, I rely on a CES-production function that allows for a richer and more flexible framework compared to the usual Cobb-Douglas one. In an urban context, Baum-Snow et al. (2018), Davis et al. (2020) and Eeckhout et al. (2021) also rely on CES production functions to guide their analysis of the rising inequality between skilled and unskilled workers in a spatial context. Here, I account for differences across firms in the composition of their workforce but I focus on the substitutability between capital and labor instead of the substitutability between different types of workers.

The paper is organized as follows. I present the data and several motivating stylized facts in Section 2. I estimate the density-elasticity of the firm-level labor share in Section 3. In Section 4, I propose a theoretical framework to structurally interpret these empirical results and I come back to the data to investigate the determinants driving the sectoral heterogeneity of the density-elasticity of the firm-level labor share. I discuss the implications of my results for firms' location decisions in Section 5. Finally, Section 6 concludes.

2 Data and descriptive statistics

In this section, I present the French data I use and several descriptive statistics on the differences in terms of labor share observed across both firms and space.

2.1 The data

The main dataset used in this paper is the French Annual Business Surveys (*"Enquêtes Annuelles d'Entreprises"*, hereafter EAEs) for the period 1996-2006. This administrative dataset provides balance-sheet information for all of the firms bigger than 20 employees. The 20-employee threshold eliminating many more firms in services than in manufacturing, the EAEs are far less representative for services. This is why I focus on manufacturing industries.[5] The list of 3-digit industries included in the final regression sample is available in Table 5 in Appendix A. Among other variables, the EAEs crucially record firm-level total wage bill (inclusive of all worker and employer contributions), number of employees, value-added and 3-digit industry code. Total wage bill gives the portion of the firms' value-added that goes to workers, and I define the total income that goes to capital as the firm-level value added minus total wage bill. Unless otherwise stated, I will use as the main variable of interest throughout the paper the relative labor share, i.e. the ratio of labor income (total wage bill) to capital income (value added minus total wage bill). For the sake of concision, I will often simply call it the labor share. As will become clear with the conceptual framework in Section 4, compared to the ratio of labor income to value added, this variable lends itself better to a structural interpretation of the regression results.[6] Since the local competitive prices of labor and capital are not directly observable, my measure of relative labor share includes the markups and the markdowns firms might apply to the prices they charge and the wages they pay. I discuss later in Section 3.1 the empirical issues this is raising and the way I address them. The EAEs also record the municipality where firms are located. Each firm is thus assigned to one of the

[5]The FICUS-FARE fiscal data would be exhaustive for both manufacturing and services industries. Unfortuantely, they are not accessible outside of Europe.

[6]Firm-level value added is smaller than total wage bill for around 15% of the observations representing around 8% of total activity in the sample (as measured by value-added). This simply means that the gross operating surplus (capital income) of the firm is negative, which might happen when a firm faces a negative shock or when it applies certain fiscal deductions. Given the way it is defined, this implies that the relative labor share is negative (or equivalently the ratio of labor income to value added is bigger than 1), which does not make sense. To circumvent this issue, I focus on observations for which the relative labor share is positive.

341 local labor markets (LLM) in continental France.[7] The local environment of the firms, and in particular local employment density, will be defined at this spatial scale.

I also use exhaustive *establishment-level* social security data ("Déclarations Annuelles de Données Sociales" in French) which provide, for each establishment, its municipality, 3-digit industry and number of employees by gender and occupation (there are five occupation categories, namely "CEO and craftsperson", "Manager", "Intermediate profession", "Employee" and "Laborer"). Thanks to this information, I can calculate the aggregate employment by 3-digit industry and LLM and use it to compute the specialization of the LLM in the industry of the firm. Also, the number of workers by gender and occupation is aggregated at the level of the firm to control for the composition of the firm-level labor force.[8] Finally, this data allows to identify the firms that have establishments in several local labor markets. For these firms, the definition of their local environment is not obvious. In the benchmark results, I will measure the characteristics of their local environment as the weighted average of the characteristics of the LLMs where they have establishments, using as weights the share of each establishment in the total employment of the firm. I will also check that the results hold when focusing on firms that have all of their activity in a single LLM.

My main variable of interest at the level of LLMs is employment density. It is defined as the ratio of total employment to surface area of the LLM. Information on total employment comes from estimations made by the French national statistical institute based on the population censuses and on estimations proposed by Buda (2011).

Finally, on top of including various relevant controls, I tackle endogeneity issues when estimating the impact of local employment density on the firm-level labor share by relying on an IV strategy where current local employment density is instrumented by urban population density in the 19^{th} century (further details in Section 3.1). A database developed by the French institute of demographic studies (INED) and presented in Pumain and Rianday (1986) provides population in urban municipalities (2,500+ inhabitants) back to 1831. I use this information to calculate a measure of urban population density at the LLM-level in 1831.

I proceed to a basic cleaning of the database. All observations with missing, negative or null value added or number of employees are dropped, as well as firms from Corsica and overseas territories since they are subject to different fiscal rules. I also exclude industries with less than 200 observations over the period (which includes, in particular, tobacco, extraction/refining and fabrication of office machinery industries). I further drop the 3% distribution queues (within 3-digit industries) in terms of relative labor share to get rid of the firms with "abnormally" low or high relative labor income.

[7]Local labor markets ("Zones d'emploi" in French) are defined by the French national statistical institute (INSEE) based on observed commuting patterns so as to minimize the share of the population that works and lives in two different commuting zones. I use the 1990 definition of these local labor markets. The number and boundaries of LLMs has changed in 2010, i.e. after the end of my sample period.

[8]I do not have access to information on the firm-level wage bill by skill category, so that I cannot compute the share of each occupation in firm-level total wage bill.

2.2 Descriptive statistics

Before moving to the econometric analysis, I first show in this section that there is considerable variation in the firm-level labor share across both firms and LLMs. To facilitate the reading of these descriptive statistics, I use the ratio of labor income to value-added as a measure of the firm-level labor share, instead of the relative labor share that I use in the econometric analysis.[9]

The figures in the upper part of Table 1 show that the labor share varies greatly across firms in my sample. While it is equal to 76% on average (see the first line of Table 1), this share varies from 55% for the 10th percentile to 93% for the 90th percentile. These variations are not the mere reflection of technological differences across industries, since the labor share of a firm relative to the average in its own 3-digit industry varies from 79% for the 10th percentile to 131% for the 90th percentile. This is coherent with the fact that the average labor share exhibits much less variation across sectors than within sectors (in my sample, the mean of the sectoral labor share is 75% with a standard-deviation of 6.4%, while at the firm-level these figures are 76.5% and 15.2% respectively).

Table 1: Distribution of labor shares

	Firm-level labor share					
	p10	p25	p50	p75	p90	Mean
$(\text{Total wage bill/Value added})_{iszt}$	0.55	0.67	0.78	0.87	0.93	0.76
$\frac{(\text{Total wage bill/Value added})_{iszt}}{(\text{Total wage bill/Value added})_{st}}$	0.79	0.94	1.08	1.20	1.31	1.07
	LLM-level labor share					
	p10	p25	p50	p75	p90	Mean
$\overline{(\text{Total wage bill/Value added})_{isz}}^{z}$	0.64	0.67	0.71	0.75	0.78	0.71
$\overline{\frac{(\text{Total wage bill/Value added})_{isz}}{(\text{Total wage bill/Value added})_{s}}}^{z}$	0.93	0.97	1.02	1.07	1.11	1.02

In terms of notations, i denotes firms, s denotes 3-digit industries, z denotes LLMs and t denotes years. $(\text{Total wage bill/Value added})_{iszt}$ is the firm-level labor share and $(\text{Total wage bill/Value added})_{st}$ is the average labor share in a given industry and year.$\overline{(\text{Total wage bill/Value added})_{iszt}}^{zt}$ is the weighted average of the labor share in the LLM z (using as weights the share of each firm in the overall value added of the local labor market).

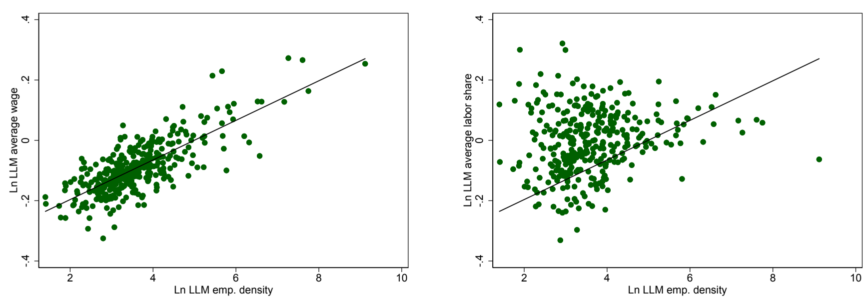
The bottom part of Table 1 displays the same statistics but averaged at the level of the 341 LLMs in the sample. The average labor share at the LLM-level varies from 64% for the 10th percentile to 78% for the 90th percentile when differences across industries are not controlled for, and from 93% to 111% when they are. Even though reduced compared to the variations across firms, these spatial variations are not negligible. As a comparison, Karabarbounis and Neiman (2014) document a 5 p.p. decline in the aggregate labor share since the mid 1970's

[9]The picture is obviously very similar when considering the relative labor share which will be used in the econometric part so as to match the conceptual framework.

in 59 countries, and Oberfield and Raval (2021) note a 15 p.p. decline of the labor share in the manufacturing industry in the US over the last few decades.

To go further in this descriptive analysis, I plot on Figure 1 the LLM average wage and average relative labor share (both in log) against the log of local employment density.[10] On the left-hand part of the figure, as extensively shown in the literature on agglomeration economies, I find a highly positive and significant correlation between local average wage and employment density. The slope of the linear fit is equal to 6.6%, well in the range of the elasticities measured in the literature when endogeneity issues are not tackled, and the R-squared of this regression is pretty high, equal to 59.6%. The graph on the right-hand side repeats the same exercise with the firm-level relative labor share. The correlation is again positive and significant, but the slope of the linear fit is much lower, equal to 1.7%, and the R-squared for this regression is very small, equal to 2.8%. The next section goes beyond correlations and digs deeper into the possible sectoral heterogeneity of these relationships.

Figure 1: Correlation of firm-level average wage and firm-level relative labor share with local employment density



Average wage | Relative labor share

Note: Average wage and relative labor share (both in logs) are net of 3-digit industry fixed effects. Each dot is a local labor market. The information displayed on this graph is the LLM average for the period 1996-2006. The slope of the linear fit for the log average wage is 6.6% (R-squared of 59.6%). The slope of the linear fit for the log relative labor share is 1.7% (R-squared of 2.8%).

3 Estimating the density-elasticity of the firm-level labor share

In this section, I first present the equation I bring to the data and how I address the endogeneity issues related to its estimation. I then discuss the results.

3.1 Empirical strategy

The equation I want to estimate is the following:

[10]The log of firm-level average wage and relative labor share are regressed on 3-digit industry-year fixed effects and LLM-year fixed effects. The LLM-year fixed effects are retrieved, averaged at the LLM-level for the whole 1996-2006 period and plotted against the average local employment density over the same period.

$$\text{Ln}\left(\frac{\text{Total wage bill}}{\text{Value added - Total wage bill}}\right)_{iszt} = \beta \text{Ln emp. density}_{zt} \left(+\gamma \text{X}_{i(sz)t}\right) + \omega_{st} + \epsilon_{iszt} \qquad (1)$$

where i denotes the firms, s the 3-digit industries, z the LLMs and t the years. $\text{X}_{i(sz)t}$ is a vector of firm and/or LLM and/or industry characteristics that I detail below. Note that given the presence of industry-year fixed effects, the estimation is based on variations of the variables between firms within a given industry and year. As is often the case in the literature on the estimation of agglomeration economies, I do not exploit variations over time as they are too modest to capture the kind of mechanisms I am after.

Firms' monopoly power. The proxy I use for capital income is value added minus total wage bill, which includes markups in case firms have market power on the output market. High-markup firms are by definition low-labor share firms. Since firms in denser areas are more productive and high-productivity firms are generally high-markup firms, not controlling for markups likely creates a downward-bias in the estimation of β. To address this issue, I introduce in the regression the log of the firm-level market share on the output market. This market share is measured as the share of the firm in the value-added of its 3-digit industry at the national level in a given year. Indeed, most models with strategic interactions deliver at equilibrium a firm-level relationship between markups and market shares (Edmond et al., 2022). I expect the correlation between firm-level labor share and firm-level market share to be negative.[11]

Composition of the workforce. Frictions on labor markets give some workers bargaining power to negotiate wages above their marginal productivity. This bargaining power might vary across different types of workers. For example, Cahuc et al. (2006) show that highly skilled workers have some bargaining power in France (even though it is modest), while low- and medium- skilled workers do not. All else equal, firms that employ more high-skilled workers should thus have a higher labor share. On the other hand, it has also been shown that highly skilled workers disproportionately locate in denser places (Combes et al., 2008). Not controlling for the firm-level composition of the workforce in terms of skills could then generate an upward bias in the estimation of β. On the opposite, firms in bigger cities employ a higher share of women, and women suffer from a wage penalty on the labor market. This may generate a downward bias in the estimation of β. I observe in the data the composition of the firm-level workforce in terms of five broad occupations (see Section 2.1 above), which partly reflect different levels of skills, and in terms of gender. I then control for the share of each occupation-gender cell in the total number of employees of the firms.[12]

[11] Results are robust when using a more flexible polynomial function of firm-level market share.

[12] Skills and gender interacting with unionization (Card et al., 2020), these controls indirectly account for differences across firms in terms of role of the unions too.

Firms' monopsony power. Manning (2010) shows that denser labor markets are more competitive, i.e. less monopsonistic, which explains (at least partly) why we observe both bigger establishments and higher wages in denser places. Lower monoposony power meaning a higher labor share, not controlling for it will lead to an upward bias in the estimation of β. To control for the fact that denser places are less monopsonistic, I introduce in the regression the log of a Herfindahl index of local labor market concentration computed at the level of each LLM and 2-digit sector.

Additional controls. As standard now, besides local employment density, I introduce among the controls the surface area of the LLM so as to distinguish density from size effects (denser LLMs being on average bigger). I also control for the share (in log) of local employment in the 3-digit industry of the firm to account for localization economies (intra-sectoral externalities). Firms bigger than 50 employees facing specific labor regulations in France that increase their labor costs (Gourio and Roys, 2014; Garicano et al., 2016), I control for a dummy identifying the firms with 50+ employees. Finally, as mentioned above, some firms have establishments in several LLMs and for them, the value of a given local characteristic (density, specialization etc.) is the weighted average of this characteristic in the LLMs where they have plants (using as weights the share of each establishment in the total employment of the firm). To account for potential measurement error, I include a dummy identifying these firms, and I also check that the results hold when I exclude them from the sample.

IV strategy. Despite the inclusion of all the previously discussed controls, there could remain endogeneity issues if temporary shocks affect both local employment density and firm-level labor shares. I follow a well-established IV strategy and use local urban population density in 1831 as an instrument for current local employment density (e.g. Ciccone and Hall, 1996; Combes et al., 2008). As long as the unobserved determinants of the firm-level labor share in dense areas in 1831 are not correlated with those at the end of the 20^{th}-beginning of the 21^{st} century, this instrument is a valid one. This is my identifying assumption here.

Finally, since I regress individual outcomes on aggregate characteristics, I cluster standard errors at the LLM-year level (Moulton, 1990).

3.2 Pooled results

I first estimate Equation (1) pooling all the industries together. The results on the main regressors of interest are displayed in Table 2 (the full set of coefficients is available upon request). Column (1) corresponds to a simple OLS regression where the only control, beyond the proxies for agglomeration economies, is the dummy identifying single-LLM firms. The raw correlation between local employment density and the firm-level labor share is negative. The coefficient becomes positive and significant in column (2) when I introduce controls for the various sources of bias mentioned above. This is due, in particular, to the introduction of controls for the monopoly power of the firm on its output market and for the specific labor laws 50+ firms are subject to, which are respectively negatively and positively related to the firm-level labor share. In column (3), even though reduced, the IV coefficient on local density remains positive and significant. When focusing on firms that have all of their establishments located in the same local labor market, local density still affects positively the firm-level labor share, and the coefficient is even boosted. However, pooling all the industries together, the elasticity I obtain is quite small. Using the results in column (3) of Table 2, I find that a one standard-deviation increase in local employment density causes an increase in the firm-level labor share by 3.6% of a standard deviation. This positive but small elasticity may mask ample heterogeneity across industries. This is what I investigate in the next section.

Table 2: Density-elasticity of the firm-level labor share - Pooled results

	$\text{Ln}\left(\frac{\text{Total wage bill}}{\text{Value added - Total wage bill}}\right)_{iszt}$			
	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Ln Emp. density$_{zt}$	-0.031^a	0.029^a	0.021^a	0.034^a
	(0.003)	(0.003)	(0.006)	(0.008)
Ln Specialization$_{szt}$	-0.050^a	-0.013^a	-0.015^a	-0.010^a
	(0.003)	(0.002)	(0.002)	(0.003)
Ln Surface area$_{zt}$	-0.027^a	-0.017^a	-0.025^a	-0.019^c
	(0.004)	(0.004)	(0.007)	(0.010)
Observations	192,012	192,012	192,012	154,944
R-squared	0.004	0.194	n.a.	n.a.
Kleinbergen-Paap F test	n.a.	n.a.	229	228.8
Sector (3-digit)-year fixed effects	yes	yes	yes	yes
Workforce composition	no	yes	yes	yes
Monopsonistic power	no	yes	yes	yes
Monopolistic power	no	yes	yes	yes
Specific labor laws	no	yes	yes	yes
Sample of firms	All	All	All	Single-LLM

Standard errors clustered at the LLM-year level in parentheses. ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1. All regressions but regression (4) include a dummy identifying single-LLM firms. The controls for the composition of the workforce include the shares (in log) of CEO and craftspersons, managers, intermediate professions, employees and laborers, all computed by gender. The control for monopsony power is a Herfindahl index of local labor market concentration (based on the firm-level shares in the total employment of the LLM). The control for monopolistic power is the firm-level share (in log) in the national sales of its 3-digit sector in a given year. The control for specific labor laws firms are exposed to is a dummy identifying firms with 50+ employees.

3.3 Sectoral results

I estimate the benchmark specification (column (3) of Table 2) separately for each 3-digit industry.[13] Figure 2 displays the coefficients obtained on local employment density. Panel (a) corresponds to estimations where all firms are included, while single-LLM firms only are kept in Panel (b). For expositional purposes, sectors are ranked so that the point estimate of the

[13] I use the French classification of indutries "Nomenclature d'activités françaises", NAF. The name of the industries is available in Table 5 in Appendix A.

coefficient based on the whole sample of firms goes in ascending order moving from the left to the right of the figure. The coefficients are highly heterogeneous across industries, confirming that the average elasticity estimated on the pooled sample hides significant differences across industries. This explains why the coefficient on density is so small, both statistically and economically, when it is estimated with industries all pooled together. Moreover, whether firms with establishments in several LLMs are excluded or not does not change much the picture: the Spearman rank correlation between sectoral coefficients across both samples is equal to 90%.

Thanks to these coefficients, I identify three groups of industries (the detailed classification is available in Table 5 in the Appendix A): an industry is said to have a negative (resp. positive) density-elasticity of the labor share if the coefficient on local employment density that appears in Figure 2 is significantly negative (resp. positive) in at least one of the two samples considered in the analysis (all firms or single-LLM firms). Based on this definition, 11 industries (representing 17% of the workforce employed in the industries of my sample) exhibit a significantly negative elasticity of the firm-level labor share to local employment density in at least one of the two samples. 29 industries accounting for 33% of the worforce exhibit a significantly positive density-elasticity of the firm-level labor share in at least one of the two samples. Finally, in 50 industries (50% of the workers), the firm-level labor share does not significantly vary with local employment density in both samples. Overall, 50% of the workforce is employed by firms whose factor shares vary depending on where they chose to locate.

In unreported regressions (results available upon request), I check whether the industries in each of the three groups exhibit specific characteristics. To do so, I regress several firm-level outcomes averaged at the 3-digit industry level on dummies identifying whether the sectoral density-elasticity of the labor share is positive or negative. Industries in which the firm-level labor share increases with local employment density exhibit lower average wages and employ fewer managers. Apart from this, nothing distinguishes the industries in which the firm-level labor share significantly varies with local employment density from the others.

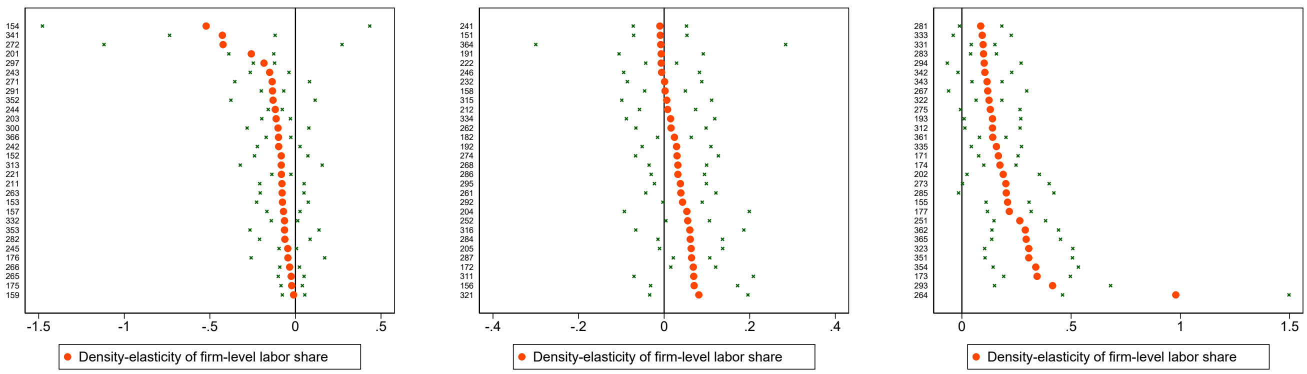
In the next section, I provide a conceptual framework that is able to rationalize the sectoral patterns of the density-elasticity of the labor share.

4 What drives the elasticity of firm-level labor share to local employment density?

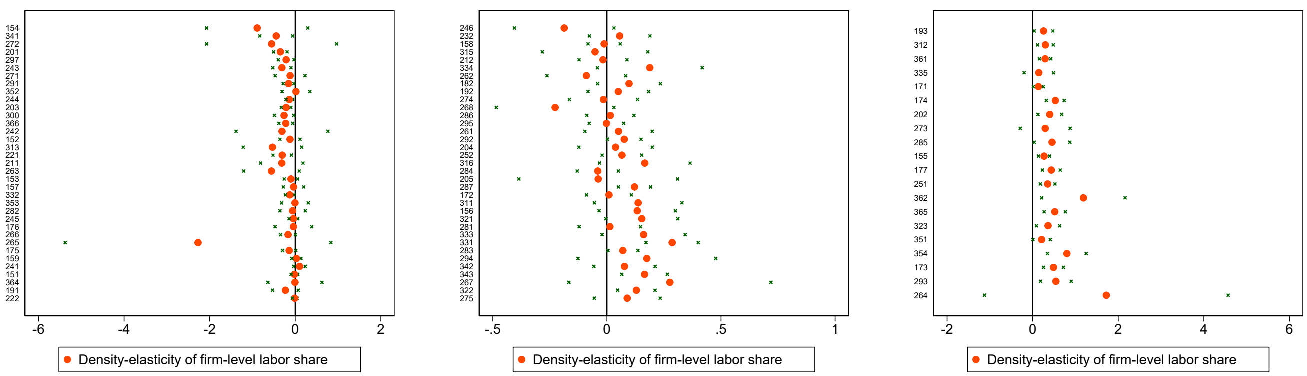
The framework I propose relates the density-elasticity of the firm-level labor share to the elasticity of substitution between production factors and to the density-elasticity of their productivity-adjusted relative cost. I use this framework to come back to the data and uncover what drives empirically the sectoral heterogeneity in the density-elasticity of the firm-level labor share.

Figure 2: Density-elasticity of the firm-level relative labor share by 3-digit sector

(a) All firms



(b) Single-LLM firms



Note: The density-elasticity of the firm-level relative labor share is estimated using the specification of column (3) in Table 2. The green crosses give the 10% confidence intervals. In both panels, industries are ranked (from the left to the right) in ascending order of the density-elasticity of the firm-level labor share as estimated when keeping all firms in the sample. The name of the industries appears in Table 5 in the Appendix A.

4.1 Conceptual framework

Markets are assumed to be competitive so that firms are price-takers on both the output and the input markets. Market imperfections were accounted for in the empirical analysis, but they are not needed for the point I want to make here. In terms of notations, s stands for the industry firm i belongs to and z for the LLM it is located in.

Firms produce with the following production function:

$$\mathrm{Y}_i = \mathrm{A}_i \left(\alpha_s \left(\kappa_i \mathrm{K}_i \right)^{\frac{\sigma_s - 1}{\sigma_s}} + \left(1 - \alpha_s \right) \left(\lambda_i \mathrm{L}_i \right)^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{2}$$

where Y_i, K_i and L_i are the firm-level value added, capital stock and number of workers; A_i is a Hicks-neutral productivity parameter, while κ_i and λ_i are capital- and labor- augmenting productivity parameters. α_s measures how much capital contributes to production and σ_s is the sectoral elasticity of substitution between capital and labor. I assume σ_s>0, i.e. capital and labor are imperfect substitutes in the production function, as well as constant returns to scale. Note that we can think of capital as a bundle of different types of capital (machinery, land etc.). However, since there is no distinction between different types of capital in the data I use, I keep the framework as simple as possible. In the same vein, labor can be thought as a bundle of workers with different skills, but worker heterogeneity is not explicitly modeled since I do not have data on the distribution of the firm-level total wage bill across different types of workers.[14]

Note that the paper is focused on how the local surplus of income attributable to agglomeration economies is shared between labor and capital. As done in most of the papers interested in the evolution of factor shares over time (be it at the aggregate level or at the firm-level), I thus use a value added production function and I ignore intermediate materials. It may be the case that the use of materials, be they sourced domestically or internationally, varies across firms, sectors and/or cities. These variations may be interesting in their own right, but they should not affect the way the value added generated locally is distributed between capital and labor.

I note w_z and r_z the wage and the rental rate faced by firms in local labor market z, which amounts to assuming that factor markets are integrated across industries within a given local labor market. I note p_s the output price in industry s, which means that output markets are assumed to be perfectly integrated at the national level.[15] Then, the FOCs of the firm-level profit maximization problem yield the following expressions:

$$\mathrm{w}_z = (1-\alpha_s)\left(\mathrm{A}_i\lambda_i\right)^{\frac{\sigma_s-1}{\sigma_s}}\left(\frac{\mathrm{p}_s\mathrm{Y}_i}{\mathrm{L}_i}\right)^{\frac{1}{\sigma_s}} \tag{3}$$

$$\mathrm{r}_z = \alpha_s\left(\mathrm{A}_i\kappa_i\right)^{\frac{\sigma_s-1}{\sigma_s}}\left(\frac{\mathrm{p}_s\mathrm{Y}_i}{\mathrm{K}_i}\right)^{\frac{1}{\sigma_s}} \tag{4}$$

Computing the ratio (4)/(3) and rearranging the expression, it comes that:

$$\frac{\mathrm{K}_i}{\mathrm{L}_i} = \left(\frac{\alpha_s}{1-\alpha_s}\right)^{\sigma_s}\left(\frac{\lambda_i}{\kappa_i}\right)^{1-\sigma_s}\left(\frac{\mathrm{w}_z}{\mathrm{r}_z}\right)^{\sigma_s}$$

and thus:

$$\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i} = \left(\frac{1-\alpha_s}{\alpha_s}\right)^{\sigma_s}\left(\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i}\right)^{1-\sigma_s} \tag{5}$$

The ratio $\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i}$ is the relative share of labor in overall value added of firm i. It decreases with α_s: α_s being the parameter that governs the contribution of capital to production, this just means that the labor share is higher in more labor-intensive industries. More interestingly, the labor share is a function of $\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i}$, which is the relative cost of labor adjusted for factor-

[14]In papers dealing with wage inequality, worker heterogeneity is modeled such that skilled and unskilled labor are interchangeably nested with capital (see, e.g., Baum-Snow et al., 2018).

[15]Since I am interested in the relative factor shares in overall value added, output price does not play any role. Hence, this assumption is not crucial in the end.

augmenting productivity. Whether the labor share increases with the relative cost of labor depends on σ_s. If σ_s is equal to 1, we are back to the Cobb-Douglas production function and the relative labor share is constant (equal to $\frac{1-\alpha_s}{\alpha_s}$). If σ_s>1, the labor share decreases when the relative cost of labor increases: indeed, when labor becomes relatively more expensive, firms substitute capital for labor more than proportionately compared to the variation in its relative cost. Finally, if 0<σ_s<1, the labor share increases with the productivity-adjusted relative cost of labor since firms substitute capital for labor when the latter becomes relatively more expensive, but less than proportionately.

It follows from Equation (5) that the impact of agglomeration economies on the firm-level labor share is the combination of two things that may both vary across industries: i) how agglomeration economies affect the relative cost of factors adjusted for factor-augmenting productivity; ii) how firms adjust their factor mix to the relative cost of factors. More formally, after taking the log of Equation (5), it comes that:

$$\mathrm{Ln}\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i} = \sigma_s\mathrm{Ln}\frac{1-\alpha_s}{\alpha_s} + (1-\sigma_s)\mathrm{Ln}\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i} \tag{6}$$

Focusing on the agglomeration economies that stem from local employment density Dens_{zt}, Equation (6) implies that the density-elasticity of the relative labor share $\theta_{\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i},\mathrm{Dens}_{zt}}$ is equal to $(1-\sigma_s)\times\theta_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$.[16] I can thus structurally interpret the parameter β of Equation (1) estimated in Section 3 as being equal to $(1-\sigma_s)\times\theta_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$. Since λ_i and κ_i are not observable, $\theta_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$ cannot be directly estimated. However, recovering an estimate of σ_s, it becomes possible to infer $\widehat{\theta}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},Dens_{zt}}$ as being equal to $\frac{\widehat{\beta_s}}{1-\widehat{\sigma_s}}$ and identify the drivers of the sectoral heterogeneity in the density-elasticity of the firm-level labor share. This is what I do in the next subsection.

4.2 Back to the data

From now on, I work at the level of the three broad categories of industries identified in Section 3, i.e. industries with a negative, null or positive density-elasticity of the firm-level labor share. Indeed, the estimation of substitution elasticities becomes noisy at a more disaggregated level of the sectoral nomenclature.

Guided by Equation (6) of the conceptual framework and following Raval (2019) and Oberfield and Raval (2021), I estimate the following equation:

$$\mathrm{Ln}\left(\frac{\text{Total wage bill}}{\text{Value added - Total wage bill}}\right)_{is'szt} = \gamma_{s'}\mathrm{Ln}\ \mathrm{w}_{zt} + \beta_{s'}\mathrm{X}_{it} + \omega_{st} + \epsilon_{is'zt} \tag{7}$$

where s is the 3-digit industry of the firm and s' is the broad sector category at the level of which I estimate the elasticity of substitution. The parameter $\sigma_s\mathrm{Ln}\frac{1-\alpha_s}{\alpha_s}$ in Equation (6) is absorbed by the sector-year fixed effects ω_{st}, and through the lens of my framework, $\gamma_{s'}$=1-$\sigma_{s'}$.

[16] $\sigma_s\mathrm{Ln}\frac{1-\alpha_s}{\alpha_s}$ being by definition constant and specific to each industry s.

The estimation of Equation (7) raises a number of issues. In particular, I regress the firm-level relative labor share on the local average wage while according to theory, the exact cost to take into account is the relative cost of labor adjusted for factor-augmenting productivity $\frac{\mathrm{w}_{zt}/\lambda_{it}}{\mathrm{r}_{zt}/\kappa_{it}}$. The rental cost of capital and the relative factor-augmenting productivity of firms are thus in the residual, which creates endogeneity. I tackle this issue thanks to an IV strategy inspired by the recent literature on the estimation of CES production functions. In short, I instrument the local average wage by its predicted level considering: *i*) the share of each sector in local employment in 1996; *ii*) the yearly employment growth of each sector at the national level; *iii*) the sectoral average wage in 1996. The logic of the instrument can be summarized as follows: in each year, those places that are specialized in high-wage industries as measured by the sectoral wage in 1996 (net of the composition of the workforce and of local fixed effects) are likely to pay higher wages due to a fiercer competition between firms to attract workers or to some kind of local Balassa-Samuelson effect. Given the way the instrument is built, it is net of local determinants of wages and of local trends in employment: it is thus arguably orthogonal to the relative factor-augmenting productivity of firms at the local level and to the local cost of capital. As long as the competition between firms to attract workers affects the local level of wages but not the returns to capital, the instrument is also orthogonal to the current local returns to capital. Another key assumption is that the initial sectoral specialization of local labor markets is unrelated to the local factor-augmenting productivities and to the local cost of capital. To reduce further the threat of endogeneity, I restrict the sample estimation to the years 2000-2006 (and thus do not include the year 1996 used for the measure of sectoral wages and the immediate subsequent years). All the details of the estimation are provided in Appendix B.

Once equipped with the elasticity of substitution between production factors, I estimate the average density-elasticity of the firm-level labor share separately for each of the three broad categories of industries; put differently, I re-estimate the specification of column (3) of Table 2 separately for each subgroup. Considering that $\theta^{s'}_{\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i},\mathrm{Dens}_{zt}} = (1-\sigma_{s'}) \times \theta^{s'}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$, I can finally infer the value of $\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$ by computing the expression $\frac{\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i},\mathrm{Dens}_{zt}}}{1-\widehat{\sigma_{s'}}}$.

The results are presented in Table 3 and convey three main messages. First, the elasticity of substitution varies greatly across the three broad categories of industries. Capital and labor are quite substitutable in the production function of industries where the firm-level labor share decreases with local employment density, the estimated elasticity being greater than 1. On the opposite, they are complements in industries where the firm-level labor share increases with local employment density: for these industries, the elasticity of substitution between capital and labor is null (Leontieff production function). Finally, in industries where the elasticity of the firm-level labor share to local density is null, the substitution elasticity between capital and labor takes intermediate values, equal to 0.7. Second, considering the way the three groups of industries are defined, the estimated density-elasticity of the firm-level labor share (third row of Table 3) has the expected sign and statistical significance for each of them. Note that in those industries where the density-elasticity is different from zero, the impact of density on the firm-level labor share is not only statistically but also economically significant.[17] Third, when combining the two previous elasticities, I find that the elasticity of the productivity-adjusted relative cost of labor to local employment density is positive (but almost equal to 0 in industries where the density-elasticity of the labor share is null). This is coherent with labor being less mobile than capital. However, how to interpet the fact that in industries where the density-elasticity of the labor share is non-null, the values taken by the density-elasticity of the productivity-adjusted relative cost of labor are well above the usual 2-3% elasticity of nominal wages to local employment density? I cannot directly estimate the density-elasticity of the returns to capital r_z with the data at hand but it is reasonable to think that it is either null (perfect mobility of capital) or slightly positive (the supply of some types of capital such as land being imperfectly elastic),[18] so that the elasticity of $\frac{\mathrm{w}_z}{\mathrm{r}_z}$ to local employment density should be smaller than 2-3%. Then, values above 2-3% for $\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},\mathrm{Dens}_{zt}}$ imply that the relative factor-augmenting productivity of labor must decrease with density, or put differently productivity-enhancing effects of agglomeration economies need to be more capital-augmenting than labor-augmenting. Since the 1990s, it is standard to assume that agglomeration economies are Hicks-neutral. My results show this assumption is unwarranted.

Table 3: Estimated elasticities

	Manuf		
$\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i},\mathrm{Dens}_{zt}}$	< 0	$= 0$	> 0
$\sigma_{s'}$	1.475 (1.020;1.930)	0.722 (0.451;0.930)	-.033 (-0.477;0.411)
$\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z\mathrm{L}_i}{\mathrm{r}_z\mathrm{K}_i},Dens_{zt}}$	-0.124^a	0.001	0.131^a
$\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},Dens_{zt}}$	0.261	0.004	0.127

The estimates of $\sigma_{s'}$ come from IV estimations described in Appendix B. The 95% confidence intervals are based on standard errors clustered at the LLM-year level.

I perform two robustness checks. I estimate the CES production functions using the social security data instead of the EAEs to measure local average wages. The results I obtain, presented in Appendix B, are very close to the benchmark ones. I also re-run the whole analysis defining the three broad categories of industries based on sectoral estimations obtained with the whole sample of firms only (Panel (a) of Figure 2), and not based on both the whole sample and the sample restricted to single-LLM firms (Panels (a) and (b) of Figure 2). Results (available upon request) are very similar, both qualitatively and quantitatively.

In the end, I have shown that the sectoral heterogeneity of the density-elasticity of the firm-level labor share is the outcome of two phenomena: *i*) the relative cost of labor adjusted

[17] A one standard-deviation increase in local employment density causes a decrease (resp. an increase) in the firm-level labor share by 28.56% of a standard-deviation (resp. on average 20.84%) when the elasticity is negative (resp. positive).

[18] To rationalize a negative density-elasticity of the returns to capital, one would need to assume important frictions on the capital market, such as heavy credit constraints, in low-density places.

for factor-augmenting productivity increases with density, but not equally across industries; *ii*) the elasticity of substitution between capital and labor varies across industries too, and it differs from 1 (the usually-assumed Cobb-Douglas case). To quantify the role of each of these two factors, I perform the following exercise. I estimate the substitution elasticity between capital and labor for the whole manufacturing industry. I find it is equal to 0.630. Considering the estimate of the density-elasticity of the firm-level labor share presented in column (3) of Table 2, equal to 0.021, this means that the density-elasticity of the relative cost of labor adjusted for factor-augmenting productivity is equal to 0.059 on average for the whole manufacturing sector.

Then, I assume that the elasticity of substitution is equal to 0.630 for all manufacturing firms, and given the values of $\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},Dens_{zt}}$ found for the three broad categories of manufacturing industries in the data (see third row of Table 3), I recompute the density-elasticity of the labor share. In the same vein, I fix $\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z/\lambda_i}{\mathrm{r}_z/\kappa_i},Dens_{zt}}$ equal to 0.059 for the whole manufacturing and using the estimated substitution elasticities that appear in the first raw of Table 3, I recompute the density-elasticity of the labor share once again. The results are displayed in Figure 3. Although reduced compared to what is found in the data, sectoral heterogeneity across industries appears in the two counterfactual analyses. Hence, differences in terms of the subsitution-elasticity between capital and labor and in terms of the density-elasticity of their relative cost both explain the sectoral heterogeneity of the density-elasticity of the labor share.

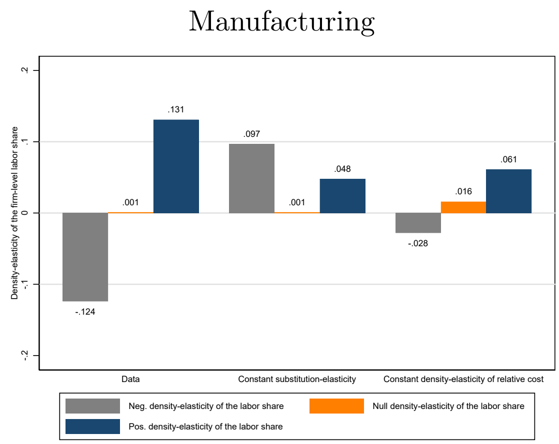
5 Density-elasticity of the firm-level labor share and the spatial sorting of firms

I investigate now the implications of the sectoral heterogeneity in the density-elasticity of the firm-level labor share for the spatial sorting of firms.

Denser places offer productive externalities to firms, but firms face higher production costs there. Using a model where heterogeneous firms produce with a Cobb-Douglas production function, and assuming that the relative cost of labor increases with city size,[19] Gaubert (2018) shows that the higher the share of labor in overall production costs, the lower the elasticity of firm-level profit to city-size. This is why denser places are especially attractive to firms in industries that are less labor-intensive. If we account for the empirical and theoretical results presented in the previous sections, the elasticity of firm-level profit to city-size does not only depend on the sectoral average labor share, but also on how the firm-level labor share varies with density. More precisely, controlling for sectoral labor intensity, the propensity to locate in denser places should be lower in industries where firms see their labor share increase with local employment density. The opposite should be true for firms in industries where the firm-level labor share decreases with local density. This is what I want to test in this section.

[19]Capital is assumed to be perfectly traded but labor is imperfectly mobile, so that the relative cost of labor increases with the demand for production factors.

Figure 3: Factors contributing to the heterogeneity of the density-elasticity of the firm-level labor share



Note: The first three bars represent the estimated density-elasticity of the firm-level labor share for each group of industries (second raw of Table 3). The three bars in the middle stand for the value of this density-elatsicity when the elasticty of substitution is assumed to be constant across industries (0.630 for manufacturing industries and 0.654 for services) but the density-elasticity of the relative cost of factors is the one found in the data (third raw of Table 3). Finally, in the last three bars, the density-elasticity of the relative cost of factors is assumed to be constant across industries (equal to 0.059) but the substitution-elasticity between factors is the one found in the data (first raw of Table 3).

Empirically, the location decision of individual firms can be analyzed thanks to logistic models where firm-level profit is the latent variable: the probability that a firm locates in a given region increases with the local characteristics that positively affect its expected profit there. Aggregating these individual decisions at the local level, firms' location decisions can also be analyzed thanks to count models (on the equivalence between conditional logit and Poisson estimators, see Schmidheiny and Brulhart, 2011). I thus estimate a Poisson model where the dependent variable is the total employment in a given industry s and LLM z at time t.[20] I use employment instead of the number of establishments to account for the fact that bigger/more productive establishments are more likely to locate in denser places (Combes et al., 2012; Gaubert, 2018). The variables of interest are local employment density in z and its interactions with four sectoral characteristics: the sectoral average labor intensity,[21] the sensitivity to agglomeration economies,[22] the sensitivity of the firm-level labor share to

[20]Total employment in a given industry s and LLM z at time t is computed thanks to the Social Security data, which are establishment-level data and are more exhaustive than the EAEs (see Section 2.1). The dataset includes zeroes, i.e. LLM-industry cells with 0 employee.

[21]Sectoral average labor intensity is proxied using the 3-digit industry fixed effects retrieved from regressions similar to the specification of column (3) in Table 2 used to estimate the density-elasticity of the relative labor share, but run separately for each broad catogory of industries as in Section 4.2.

[22]Sensitivity to agglomeration economies is proxied by a dummy equal to 1 for those 3-digit industries for which the density-elasticity of the firm-level labor productivity (value-added over employment) is positive and significant at the 10% level. The density-elasticity of the firm-level labor productivity is estimated thanks to

local density, and the share of managers in the overall sectoral workforce (to control for the higher propensity of industries that are highly reliant on skilled workers to locate in big cities). Regarding local characteristics influencing firms' location decisions, I also control for the surface area and the market potential of LLMs on top of employment density.[23] All regressions also include 3-digit industry fixed effects.

The results are reported in Table 4 and are striking. Not surprisingly, big and dense LLMs are more attractive to firms: surface area, market potential and employment density are all positively and very significantly related to the number of employees in a given industry and a given LLM.

Moreover, the results show that in line with Gaubert (2018), the attractiveness of denser places is less pronounced for industries with a high average labor intensity (negative coefficient on the interaction between local density and sectoral average labor intensity), while the opposite is true for industries that are highly sensitive to agglomeration economies (positive coefficient on the interaction between local employment density and the dummy identifying the industries where firm-level labor productivity significantly increases with local employment density). Moreover, in industries where the firm-level labor share increases (resp. decreases) with local density, firms are relatively less (resp. more) attracted to dense LLMs (the reference category being the industries where the firm-level labor share is insensitive to local density). These patterns are robust to the inclusion of the interaction between local employment density and the sectoral share of managers in the overall workforce in order to control for the fact that denser places attract disproportionately more educated workers, and thus firms employing them.

In the end, my results show that beyond the average labor-intensity of the production function, how the firm-level labor share varies with density is also a significant driver of firms' location decisions. This driver is quantitatively important. Focusing on the sensitivity of sectoral employment to local employment density, the coefficients in column (2) of Table 4 show that belonging to an industry with a positive density-elasticity of the labor share decreases the sensitivity to local density by 0.051, which is equivalent to an increase of the sectoral labor intensity by 1.47 standard-deviation.[24] In the same vein, in industries with a negative density-elasticity of the labor share, the sensitivity of location decisions to local density is higher by 0.093, which is equivalent to an increase of the sectoral labor intensity by 2.68 standard-deviation.

IV regressions where current local density is instrumented by local density in 1831. The controls include LLM surface area and specialization in the 3-digit industry of the firm, as well as dummies identifying single-LLM firms.

[23] Market potential of LLM z is proxied by the weighted sum of employment in all of the other LLMs, using as weights the bilateral distance between z and each LLM.

[24] The standard deviation of sectoral labor intensity being equal to 0.806 in the sample, the calculation is as follows: $\frac{0.051}{0.043 \times 0.806} = 1.47$.

Table 4: Density-elasticity of the firm-level labor share and spatial sorting

	# emp.$_{szt}$	
	(1)	(2)
Ln Emp. density$_{zt}$	0.688^a	1.126^a
	(0.012)	(0.026)
Ln Surface area$_{zt}$	0.893^a	0.899^a
	(0.014)	(0.014)
Ln Market potential$_{zt}$	0.218^a	0.212^a
	(0.027)	(0.027)
Ln Emp. density$_{zt}$ $\times$Average labor intensity$_s$	-0.062^a	-0.043^a
	(0.008)	(0.008)
Ln Emp. density$_{zt}$ $\times$ $\mathbb{1}$ Highly sensitive to agglo. eco.$_s$	0.071^a	0.046^a
	(0.014)	(0.011)
Ln Emp. density$_{zt}$ $\times$ $\mathbb{1}$ Positive density-elasticity of the labor share$_s$	-0.034^b	-0.051^a
	(0.016)	(0.013)
Ln Emp. density$_{zt}$ $\times$ $\mathbb{1}$ Negative density-elasticity of the labor share$_s$	0.225^a	0.093^a
	(0.024)	(0.015)
Ln Emp. density$_{zt}$ $\times$ Ln Share managers$_s$		0.167^a
		(0.011)
Observations	337,590	337,590
Industry (3-digit)-year fixed effects	yes	yes

Standard errors clustered at the LLM-year level in parentheses. ^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$.

6 Conclusion

While the urban wage premium has been largely documented in the literature, the effect of agglomeration economies on the factor mix of firms has been ignored so far. I have filled this gap here by showing that the elasticity of the firm-level labor share to local density is highly heterogeneous across industries, which reflects differences in both the substitution elasticity between capital and labor and the density-elasticity of the relative cost of production factors. These facts are important since they are incompatible with two assumptions generally made in the recent literature on agglomeration economies, namely the Cobb-Douglas production function and the Hicks-neutrality of agglomeration economies. These are not small issues, since they have important implications, both qualitatively and quantitatively, for the spatial sorting of industries, a fundamental question in the economic analysis of the spatial distribution of economic activity.

The results discussed in this paper also open avenues to think of the consequences of robotization on the spatial distribution of economic activity. Indeed, several recent papers find that capital tends to replace labor in firms that rely on automation and artificial intelligence (e.g. Acemoglu and Restrepo, 2019; Acemoglu et al., 2022), so that the elasticity of substitution between robots and labor is certainly higher than the one measured with more traditional forms of capital. On the other hand, I have shown that conditional of the density-elasticity of the relative cost of labor, the higher the elasticity of substitution between capital and labor, the lower the density-elasticity of the labor share, and thus the more likely firms to locate in dense and big cities. By increasing the elasticity of substitution between capital and labor, robotization is thus likely to reduce the strength of dispersion forces on the labor market, which should make cities even more attractive to firms.[25] I leave the formal investigation of this issue for further research.

[25]This conjecture is consistent with recent evidence in Eeckhout et al. (2021) who show that firms in big cities are more likely to adopt IT, which they explain by their greater incentive to reduce labor costs.

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Appendix

A- List of industries in the regression sample

Table 5: List of industries in the sample

3-digit code	Name	Density-elasticity of the firm-level labor share (benchmark)	Density-elasticity of the firm-level labor share (robustness)
151	Meat	0	0
152	Fish	0	0
153	Fruit and Vegetables	0	0
154	Manuf. of oils and fats	0	0
155	Manuf. of dairy prod.	+	+
156	Manuf. of grain mill prod., starches and starch prod.	0	0
157	Manuf. of feedingstuffs	0	0
158	oth. agrifood	0	0
159	Beverage	0	0
171	Spinning of textiles	+	+
172	Weaving of textiles	+	+
173	Finishing of textiles	+	+
174	Manuf. of textile prod.	+	+
175	oth. textile industries	0	0
176	Manuf. of knitted and crocheted fabrics	0	0
177	Manuf. of knitted and crocheted articles	+	+
182	Manuf. of clothes	0	0
191	Tanning and dressing of leather	0	0
192	Manuf. of luggage, handbags and the like	0	0
193	Footwear	+	+
201	Sawmilling, planing and impregnation of wood	−	−
202	Manuf. of wood−based panels	+	+
203	Manuf. of oth. builders' carpentry and joinery	−	−
204	Manuf. of wooden containers	0	0
205	Manuf. of oth. prod. of wood;	0	0
	Manuf. of articles of cork and straw materials	+	
211	Manuf. of pulp, paper and paperboard	0	0
212	Manuf. of articles of paper and paperboard	0	0
221	Publishing activities	−	−
222	Printing	0	0
232	Manuf. of refined petroleum prod.	0	0
241	Manuf. of basic chemicals and chemical prod.	0	0
242	Manuf. of agrochemical prod.	0	0
243	Manuf. of paints and varnishes	−	−
244	Manuf. of basic pharmaceutical prod. and	−	−
	pharmaceutical prep.	+	
245	Manuf. of soap and detergents, cleaning and	0	0
	polishing prep., perfumes and toilet prep.	+	
246	Manuf. of oth. chemical prod.	0	0
251	Rubber	+	+
252	Plastics	+	+
261	Manuf. of glass and glass prod.	0	0
262	Manuf. of ceramic prod.	0	0
263	Manuf. of ceramic tiles and flags	0	0
264	Manuf. of tiles and bricks, in baked clay	+	+
265	Manuf. of cement, lime and plaster	0	0
266	Manuf. of articles of concrete and plaster	0	0
267	Cutting, shaping and finishing of stone	0	0
268	Manuf. of oth. various mineral prod.	0	0
271	Manuf. of oth. non−metallic mineral prod.	0	0
272	Manuf. of tubes	0	0
273	Manuf. of oth. prod. of first processing of steel	+	+
274	Manuf. of oth. non−ferrous metals	0	0
275	Casting of metals	0	0
281	Manuf. of structural metal prod.	0	0
282	Manuf. of metallic reservoirs and central heating boilers	0	0
283	Boilermaking	+	+
284	Forging, pressing, stamping and roll−forming of metal;	0	0
	powder metal.	+	
285	Treatment and coating of metals; general mechanical engin.	+	0
286	Manuf. of cutlery, tools and general hardware	0	0
287	Manuf. of oth. fabricated metal prod.	+	+
291	Manuf. of machin.	−	−
292	Manuf. of general−purpose machin.	+	0
293	Manuf. of agricultural and forestry machin.	+	+
294	Manuf. of machine−tools	0	0
295	Manuf. of oth. special−purpose machin.	0	0
297	Manuf. of electric domestic equip.	−	−

0 means that the density-elasticity of the labor share is null, − that it is significantly negative, + that it is significantly positive. In the benchmark classification, + (resp. −) means that the density-elasticity of the labor share is significantly positive (resp. negative) when estimated on the whole sample of firms or on the sample of single-LLM firms. In the robustness classification, + (resp. −) means that the density-elasticity of the labor share is significantly positive (resp. negative) when estimated on the whole sample of firms.

List of industries in the sample (cont.)

3-digit code	Name	Density-elasticity of the firm-level labor share (benchmark)	Density-elasticity of the firm-level labor share (robustness)
300	Manuf. of office machin. and equip. (including comput.)	−	0
311	Manuf. of electric motors, generators and transformers	0	0
312	Manuf. of electricity distribution and control apparatus	+	+
313	Manuf. of wiring and wiring devices	0	0
315	Manuf. of lamps and electric lighting equip.	0	0
316	Manuf. of oth. electrical equip.	0	0
321	Manuf. of electronic components	0	0
322	Manuf. of communication equip.	+	+
323	Manuf. of television and radio receivers, sound or video record.	+	+
	or reproducing apparatus and associated goods	+	
331	Manuf. of medical and surgical equip. and orthopaedic app.	+	+
332	Manuf. of instruments and app. for measuring and control.	−	0
333	Manuf. of industrial process control equip.	0	0
334	Manuf. of optical instruments and photographic equip.	0	0
335	Manuf. of watches and clocks	+	+
341	Manuf. of motor vehicles	−	−
342	Manuf. of bodies (coachwork) for motor vehicles;	0	0
	Manuf. of trailers and semi− trailers	+	
343	Manuf. of parts and accessories for motor vehicles	+	+
351	Building of ships and boats	+	+
352	Manuf. of rolling stock	0	0
353	Manuf. of air and spacecraft and related machin.	0	0
354	Manuf. of motorcycles and bicycles	+	+
361	Manuf. of furniture	+	+
362	Manuf. of jewellry	+	+
364	Manuf. of sports goods	0	0
365	Manuf. of games and toys	+	+
366	Oth. manufacturing	−	−

0 means that the density-elasticity of the labor share is null, − that it is significantly negative, + that it is significantly positive. In the benchmark classification, + (resp. −) means that the density-elasticity of the labor share is significantly positive (resp. negative) when estimated on the whole sample of firms or on the sample of single-LLM firms. In the robustness classification, + (resp. −) means that the density-elasticity of the labor share is significantly positive (resp. negative) when estimated on the whole sample of firms.

B- Estimation of substitution elasticities

Guided by Equation (6) of the conceptual framework and following Raval (2019) and Oberfield and Raval (2021), I estimate the following equation:

$$\text{Ln}\left(\frac{\text{Total wage bill}}{\text{Value added - Total wage bill}}\right)_{is'szt} = \gamma_{s'}\text{Ln w}_{zt} + \beta_{s'}\text{X}_{it} + \omega_{st} + \epsilon_{is'zt} \tag{8}$$

where s is the 3-digit industry of the firm and s' is the broad sector category at the level of which I estimate the elasticity of substitution (i.e. industry with a negative, null or positive elasticity of the firm-level labor share to local employment density). The parameter $\sigma_s \text{Ln}\frac{1-\alpha_s}{\alpha_s}$ in Equation (6) is absorbed by the 3-digit sector-year fixed effects ω_{st}, and through the lens of my framework, $\gamma_{s'}$=1-$\sigma_{s'}$. I do not directly observe Ln w_{zt}. I compute it by regressing firm-level average wage Ln w_{iszt} on the share of the five broad occupation (by gender) in the firm-level workforce, 3-digit industry-year fixed effects and LLM-year fixed effects. The average local wages are then defined as the LLM-year fixed effects.[26] As discussed in Section 3.1, X_{it} includes the log of firm i's market share to account for the fact that the measure of relative labor share includes markups.

The estimation of Equation (8) raises a number of issues. In particular, I regress the firm-level relative labor share on the local average wage while according to theory, the exact cost

[26] Note that when estimating local average wages, I restrict the sample to single-LLM firms to reduce the possible measurement error induced by the firms who have estbalishments is several LLMs. I do not control for the Herfindahl index of local labor market concentration nor for the dummy identifying firms with 50+ employees as they are sources of spatial variations in local average wage that are useful for the estimation of $\sigma_{s'}$.

to take into account is the relative cost of labor adjusted for factor-augmenting productivity $\frac{\mathrm{w}_{zt}/\lambda_{it}}{\mathrm{r}_{zt}/\kappa_{it}}$. A simple fixed effect procedure is thus likely to deliver biased estimates of $\sigma_{s'}$ for two main reasons. First I do not observe the local cost of capital r_{zt} and I have no simple way to proxy for it.[27] Capital being arguably more mobile than labor (except for land), returns to capital should exhibit less spatial variation than wages, but I cannot entirely discard that more attractive places are places where both labor and capital are more expensive. This will tend to bias the coefficient on Ln w_{zt} downward. On the other hand, the relative factor augmenting productivity $\frac{\kappa_{it}}{\lambda_{it}}$ is not observable. This might be problematic since places where labor is more expensive in nominal terms are possibly places where its relative factor-augmenting productivity is high. $\mathrm{Ln}\frac{\kappa_{it}}{\lambda_i t}$ is thus probably negatively correlated with w_{zt}. Again, this will tend to bias the coefficient $\gamma_{s'}$ downward.

To address these endogeneity issues, I propose the following IV strategy. I retrieve the 3-digit sector-year fixed effects obtained from an equation similar to the one run for the estimation of Ln w_{zt} and I use the values for the year 1996 as a measure of sectoral wage $\widehat{\omega_s}$. I then estimate the employment in each 3-digit sector-LLM-year cell taking the employment in this cell in 1996 and considering that sectoral employment growth rate in each LLM and year is equal to the one observed at the national level for this sector-year. Doing so, I can compute the predicted share of each industry in the manufacturing employment of each LLM, $\widehat{\mathrm{emp\_share}}_{szt}$. For each LLM and year, I can then calculate a predicted local wage as the weighted sum $\sum_s \widehat{\mathrm{emp\_share}}_{szt} \times \widehat{\omega_s}$, and use it as an instrument for Ln w_{zt}. The logic of the instrument can be summarized as follows: those places that are specialized in high-wage industries as measured by the sectoral wage in 1996 (net of the composition of the workforce and of local fixed effects) are likely to pay higher wages due to a fiercer competition between firms to attract workers or to some kind of local Balassa-Samuelson effect. Given the way the instrument is built, it is net of local determinants of wages and of local trends in employment: it is thus arguably orthogonal to the relative factor-augmenting productivity of firms at the local level. As long as the competition between firms to attract workers affects the local level of wages but not the returns to capital, the instrument is also orthogonal to the current local returns to capital. Another key assumption is that the initial sectoral specialization of local labor markets is unrelated to the local factor-augmenting productivities and the local cost of capital. To reduce further the threat of endogeneity, I restrict the sample estimation to the years 2000-2006 (and thus do not include the year 1996 used for the measure of sectoral wages and the immediate subsequent years).

The estimates of $\sigma_{s'}$ I obtain are presented in Table 6. To check the robustness of my estimations, I use two alternative data sources to estimate the local average wage based on average firm-level data: the Annual Business Surveys (which are the main dataset used in the paper) and the Social Security Data (that I mainly use to measure the composition of the firm-level workforce in terms of occupations and gender). For a given broad category of

[27] After an in-depth analysis of the data, it appears that the information on capital stocks is far too noisy to obtain a reliable measure of r_{zt} based on firm-level capital stock and capital income as proxied by value-added minus total wage bill.

industries, the results are remarkably similar whatever the data source used for the estimation of local average wage. In the quantification in Section 4.2, I use the estimates based on the Annual Business Surveys data.

Table 6: Elasticity of substitution between capital and labor

	Manuf		
$\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z \mathrm{L}_i}{\mathrm{r}_z \mathrm{K}_i},\mathrm{Dens}_{zt}}$	< 0	$= 0$	> 0
	Annual Business Surveys		
$\sigma_{s'}$	1.475	0.722	-.033
	(1.020;1.930)	(0.451;0.930)	(-0.477;0.411)
	Social Security Data		
$\sigma_{s'}$	1.430	0.749	0.107
	(1.001;1.849)	(0.378;1.020)	(-0.310;0.524)

$\widehat{\theta^{s'}}_{\frac{\mathrm{w}_z \mathrm{L}_i}{\mathrm{r}_z \mathrm{K}_i},\mathrm{Dens}_{zt}}$ is the elasticity of the firm-level labor share to local employment density. The estimates of $\sigma_{s'}$ come from IV estimations described in Appendix B. The 95% confidence intervals are based on standard errors clustered at the LLM-year level.