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Heterogeneity in the productivity of French construction firms: A multilevel analysis

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Abstract

This paper examines how local and firm-level factors influence the productivity (labour productivity and total factor productivity) of French construction firms. We use a multilevel model to disentangle firm-specific and location-specific effects. The results cover the period 2009-2019 and confirm the importance of firm-specific determinants of productivity, mainly age and size. Our results also emphasise the influence of location and local characteristics. We find that the local unemployment rate hurts productivity, and our results bring some evidence of the existence of positive external agglomeration effects. These findings remain robust across different firm size categories.

Keywords: French construction firms; Heterogeneity of productivity; Localisation Factors; Multilevel Models

JEL code: C31, D24 , L74, R15

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1 Introduction

Industrial dynamics models have shown significant and persistent differences in performance between firms in the same sector (Jovanovic, 1982; Hopenhayn, 1992; Ericson & Pakes, 1995; Melitz, 2003). These studies show that the firm growth trajectory is determined mainly by differences in productivity. Empirical analyses of different sectors, countries and periods have confirmed this approach (Caves, 1998; Bartelsman & Doms, 2000; Haltiwanger, 2000; Foster *et al*., 2001; Farinas & Ruano, 2005). Most of the above-mentioned work relies on individual and sometimes sectoral characteristics to explain the disparity between firms.

Inspired by geographical economics, other studies approach the subject by seeking to identify and measure the influence of context on the performance of firms. They are based on the idea that the more resource-rich a region is, the more advantageous it is for local firms (Krugman, 1991; Baldwin & Okubo, 2006; Melitz & Ottaviano, 2008). This article aims to explore this approach by examining the influence of the local context on the productivity (Labour Productivity and Total Factor Productivity) of firms operating in the French construction industry.

The case of the French construction sector (FCS) is relevant for three reasons.[1]. First, while previous research has focused on a wide variety of industrial activities, no analysis has been devoted to the French construction sector, even though it accounts for a large share of activity and production.[2]. Second, the heterogeneity of the companies involved is exceptionally high. The structure by firm size of the sector exhibits a bimodal distribution which changes according to the regions: dense areas mainly host large companies, whereas small companies dominate in remote areas. Finally, the sector is frequently cited for its low contribution to the evolution of national productivity.

Contrary to many empirical models that introduce location as a control variable, we rely here on research that focuses on this geographical dimension and that, to explore it, uses a so-called multilevel approach. It consists of introducing, into the same equation, variables of a different nature (individual and local), which are treated simultaneously, thus making it possible to measure the influence of individual factors and local characteristics. Another novelty of the paper lies in the introduction of two alternative measures of productivity, labour productivity and total factor productivity (TFP). The last one is estimated at the firm level using the Ackerberg, Caves and Frazer (2015) approach.

Using individual accounting data from 78,598 firms in the construction sector over the period 2009-2019, i.e., 446,593 observations, we develop a multilevel model at the scale of the 287 labour market areas of metropolitan France[3]. Our results show that while individual firm characteristics are important in explaining their level of productivity (LP and TFP), their location also plays a significant role in explaining the observed differences. The effect at the labour market area level amounts to over 21% for labour productivity and 17% for TFP.

[1] For convenience, this paper introduces four acronyms: FCS for the French Construction Sector, LP and TFP for Labour and Total Factor Productivity and ACF for Ackerberg, Caves, and Frazer (2015).

[2] According to the National Institute of Statistics and Economic Studies (INSEE), in 2017, the French construction sector included 471,300 companies and employed 1,309,300 full-time equivalent employees.

[3] INSEE defines the labour market area ("zone d'emploi" in French) as a geographical area within which most employees reside and work, and in which establishments can find an ample supply of labour for the jobs offered. Since 2020, there have been 287 labour market areas in mainland France.

Our analysis incorporates individual factors from the literature, such as firm age, firm size and human capital, to which we add two control variables: operating subsidies per turnover and the firm's self-financing capacity to capture, at least partly, the firm strategy. We add local variables such as employment density, unemployment rate and median income for the geographical area to depict the local context. Our results show an inverted U-shaped relationship between the firm size and the productivity level, whereas the relationship between firm age and productivity is strictly decreasing. Both productivity indicators increase with human capital and the company's self-financing capacity while operating subsidies per turnover have a mixed effect depending on the type of productivity considered. We also show that local context matters. Indeed, the local unemployment rate has a negative influence on firm productivity. Conversely, the employment density, which measures agglomeration effects and local wealth approximated by median income, positively influences TFP only.

The article is structured as follows. Section 2 presents some theoretical and empirical studies on the subject, which leads us to formulate the hypothesis to be tested. Section 3 describes the empirical strategy, including data, variable definitions and the multilevel model. Section 4 includes results, discussions and robustness tests. Section 5 concludes.

2 Literature and hypotheses

2.1 Firm and local context

The relationship between location and firm performance can be traced back to the work of Marshall (1920). He provided the first in-depth economic analysis of urban economies, arguing that cities improve productivity by allowing labour market pooling, specialised suppliers and knowledge spillovers.

Numerous theoretical and empirical research explored the relationship between geography and firm performance. This field of research was opened by Malecki (1985) first and, some years later, by Krugman (1991), who shows that a geographical area with a relatively large non-rural population is attractive because of the large local market and the availability of goods and services produced which results in the concentration of the population in a small number of areas. Audretsch and Feldman (1996) confirmed the positive influence of agglomeration effects, who show that innovative activity tends to be more concentrated in industries where knowledge spillovers play a decisive role.

A complementary literature examining city growth also considers this relationship (Glaeser et al., 1992; Rosenthal & Strange, 2003). The authors show that growth is influenced not only by the spatial concentration of economic activity but also by how it is organised.

Considering the spatial variability in labour productivity of Italian SMEs during 2005, Fazio and Piacentino (2010) suggest that the environment and its evolution contribute to the observed rates. In the same vein, Raspe and van Oort (2011), using survey data covering 2009 manufacturing and service firms in the Netherlands in 2005, establish a link between productivity and the knowledge-intensive spatial contexts whose origin lies in the interplay of agglomeration externalities. New evidence is provided by Aiello et al. (2014), who analyse to what extent the characteristics of Italian manufacturing companies and regional factors affect the heterogeneity of the TFP. Using data from 2004 to 2006, they show that regional infrastructure endowment, the efficiency of local government and R&D investments positively affect business performance. Last but not least, Aiello and Ricotta (2016) analyse the heterogeneity of the TFP[4] using manufacturing firms operating in seven EU countries (Austria, France, Germany, Hungary, Italy, Spain and the UK) in 2008. The results show that 85% of the heterogeneity in productivity is due to company-specific characteristics and that the effect of location in the different European regions explains about 5% of the heterogeneity of the TFP of companies.

The explanation of productivity heterogeneity was also analysed outside the European area in the study carried out by Amara and Thabet (2019) on Tunisian manufacturing companies between 1998 and 2004. They show that the individual characteristics (age, size, capital intensity, human capital, R&D...) of the company and the regional context have a significant effect on both TFP[5] and LP.

These considerations lead us to formulate our first hypothesis:
H1. *Combining individual and local levels explains firm productivity more accurately than individual characteristics alone.*

2.2 Local characteristics and firm productivity

Local economic conditions play a critical role among the various local factors influencing firm productivity. Understanding these relationships is pivotal, as firms are embedded in localised ecosystems that exert significant, though heterogeneous, effects on their efficiency and competitiveness. Following the literature, we consider three critical local factors, the unemployment rate, the external agglomeration effects, and the available income.

The unemployment rate is identified as a potential determinant of firm productivity, albeit with conflicting results (Weisskopf, 1987; Barnichon, 2010). On one hand, higher unemployment may dampen productivity by signalling weaker local demand and reducing firms' ability to invest in advanced technologies. On the other hand, a surplus of labour in high-unemployment areas may lower wage pressures, enabling firms to allocate resources more efficiently, thus enhancing productivity.

At the firm level, high local unemployment rates can affect the quality and stability of the workforce. Firms operating in areas with lower unemployment rates may benefit from a more skilled and stable workforce, which can enhance their productivity. Conversely, high unemployment can lead to a surplus of labour, but it may also indicate a weaker local economy, limiting demand and potentially affecting firm performance negatively (Barrett et al., 2024).

Considering small firms, the local labour market dynamics also play a significant role. In periods of high local unemployment, small firms may face different challenges compared to large ones. During economic expansions, small firms may struggle to hire and retain workers due to competition from larger firms, which can lead to reduced employment even in tight labour markets. This can negatively impact firm productivity as small firms may not be able to maintain or enhance their workforce quality and quantity effectively

These previous results lead us to raise a second hypothesis:
H2. *The local unemployment rate has a negative effect on firms' productivity.*

[4] TFP was calculated using the Levinsohn and Petrin method (2003)
[5] TFP is calculated from Olley and Pakes (1996).

A second factor that has long been recognised as a driver of productivity growth comes from external agglomeration effects arising from the geographical clustering of firms (Marshall, 1920; Glaeser et al., 1992). These economies can be categorised into two main types: diversification and specialisation externalities. The first ones occur when firms benefit from being located in areas with a diverse range of industries. This diversity can lead to cross-fertilisation of ideas, innovation, and access to a broader pool of skills and services. Studies suggest that these externalities operate at a higher spatial scale, such as the municipality or city level, particularly for high-tech and knowledge-intensive industries. Specialisation externalities arise when firms in the same or close industries cluster, leading to knowledge spillovers, shared suppliers, and a thicker labour market. These externalities tend to operate at a finer level, such as within neighbourhoods or even smaller areas like postcode districts or sectors (Lavoratori & Castellani, 2021; Melo et al., 2009).

Empirical studies using firm-level data have consistently shown that firms located in larger, denser regions are more productive than those in sparse areas. This difference is attributed to the benefits of agglomeration, including better access to skilled labour, suppliers, and knowledge spillovers (Andersson & Lööf, 2011).

It comes from these elements as a third hypothesis.
H3. *Firm productivity positively correlated with geographic employment density.*

We finally consider the locally available income as another factor driving firm productivity. A higher median income in an area can led to increased demand for goods and services, which can positively impact firm productivity. When local incomes are higher, firms can benefit from a broader and more stable market, allowing them to operate more efficiently and invest in productivity-enhancing activities. Moreover, areas with higher median incomes often have a more skilled and educated workforce. Firms in these areas exhibit higher productivity as they access more skilled human capital than others.

Studies have shown that firms located in regions with higher average incomes and education levels tend to have higher productivity due to the availability of a more skilled labour force (Criscuolo et al., 2021). Higher median incomes can also be associated with better infrastructure and public services, crucial for firm productivity. Higher-income regions often invest more in transportation, communication, and other public services that facilitate business operations and enhance productivity (Faggio et al., 2010).

From this literature, we propose a fourth hypothesis.
H4. *A higher median income in an area positively influences firm productivity.*

3 Empirical strategy

3.1 Data sources and definitions

We evaluate the influence of the local context on firms' productivity in mainland France's construction sector[6]. Our dataset results from the merging of several datasets.

Production factors data come from the ESANE Results Approach File (FARE or "Fichier Approché des Résultats ESANE”). These are individual accounting data which unify the annual business surveys (EAE or “enquêtes annuelles d’entreprise”) with the unified system of business statistics based on tax returns (SUSE or “système unifié de statistique d’entreprise”). These data have the advantage of facilitating the analysis of the production system from different angles: output, inputs, income statement and balance sheet, firm performance, etc.

From the FARE dataset, we have extracted 78,598 companies over the period 2009-2019. Following Ackerberg et al. (2015), we work on an unbalanced panel covering a sample of 446,593 observations to mitigate selection bias. We eliminate all firms without employees to avoid the overrepresentation of self-entrepreneurs in a sector already rich in micro-firms. Then, we make sure that a firm is recorded for at least three consecutive years[7].

To calculate TFP, we use total gross production rather than value-added as an output variable because the role of intermediate inputs is fully recognised, which is not the case when using value-added. In addition, multifactor productivity (MFP), which uses labour, capital, and intermediate inputs, is the most appropriate tool for measuring technological change at the firm level (Schreyer & Pilat, 2001). In addition, our sample is relatively large. This precision allows us to circumvent MFP's difficulties using labour, capital, and intermediate inputs. The number of full-time equivalent employees measures the labour input. Gross fixed assets approximate the capital stock. We measure intermediate inputs as the difference between total gross output and value added at factor cost.

Since the output variables are nominal values, we deflate them using price indices for the French construction sector obtained from the STAN (STructural ANalysis) 2020 edition database (constant 2015 prices) to obtain real values. We apply these deflators to value-added, output, investment, capital, and intermediate inputs.

3.2 Dependent variable

In this paper, our dependent variable measuring the economic performance of firms is the productivity. Productivity is one of the most used economic indicators to measure the economic performance of a company. It assesses the efficiency with which resources are transformed into products and services and allows to follow the evolution of a company and to know where it stands compared to previous years. Productivity therefore reflects the financial health of the entity concerned.

We use two dependent variables: labour productivity (LP) and total factor productivity (TFP). Labour productivity is measured by the ratio between real gross value added and the number of full-time equivalent employees. Consistent with the work of Kané (2022) and Kane

[6]. The construction sector corresponds to NACE Rev. 2.1 Section F, which includes real estate development, construction of residential and non-residential buildings, civil engineering and specialised construction work.

[7] This constraint is essential to calculate productivity growth rates.

and Lopez (2023), we use the Ackerberg, Caves and Frazer (2015) method called "ACF" to estimate TFP in FCS.

Firm-level TFP is estimated using the following log-linear form of a Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \gamma l_{it} + u_{it} \tag{1}$$

with *i = 1,…….N* firms, *t = 2009, ……2019* and where the logarithm of the gross output per worker (y_{it}) depends on the logarithm of capital and intermediate input intensities (k_{it}, m_{it}) as well as of labour (l_{it}), with $\gamma = (\beta_l + \beta_k + \beta_m - 1)$ measuring the return to scale. The coefficient β_0 measures the average efficiency and u_{it} represents the deviation of firm *i* from this average at time *t*. The error term can be decomposed into two parts:

$$u_{it} = \omega_{it} + \varepsilon_{it}$$

where the term ω_{it} represents the productivity of firm *i* at time *t* and ε_{it} is a stochastic term which includes not only the measurement error but also the shocks unobservable to firms and, therefore, do not correlate with inputs. We rewrite equation *(1)* to get the estimated equation:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \gamma l_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

Productivity ω_{it} is known to the firm, which can, therefore, decide to increase production by raising the level of inputs in the event of positive productivity shocks. This reaction raises a problem of simultaneity, which Levinsohn and Petrin (2003) have resolved by identifying demand for intermediate goods as a proxy for variations in TFP known to firms[8]. However, Ackerberg, Caves and Frazer (2015) argue that the methods of Olley and Pakes and Levinsohn and Petrin suffer from identification problems. Specifically, the authors claim that the procedures of Olley and Pakes and Levinsohn and Petrin do not correctly identify the work coefficient.[9].

Finally, we estimate equation *(2)* using ACF method so that the TFP level equals:

$$TFP_{it} = \exp\left(y_{it} - \left(\hat{\beta}_k k_{it} + \hat{\beta}_m m_{it} + \hat{\gamma} l_{it}\right)\right) \tag{3}$$

The estimates consider FCS firm and year-fixed effects over 2009-2019.

3.3 Independent variables

The explanatory variables considered in the models are designed to reflect, on the one hand, firm characteristics and, on the other hand, local characteristics.

Local variables

In line with the literature on local business climate, we examine three geographical variables (level 3) corresponding to H2-H4, i.e. the local unemployment rate, the area's employment density and the median income of the labour market area. The unemployment rate *unemp* is an

[8] Olley and Pakes (1996) use the investment to resolve the simultaneity bias. However, as several studies have shown (Van Beveren, 2012; Kane, 2022; Kane &Lopez, 2023), using intermediate goods rather than investment as a proxy for unobserved productivity has several advantages.

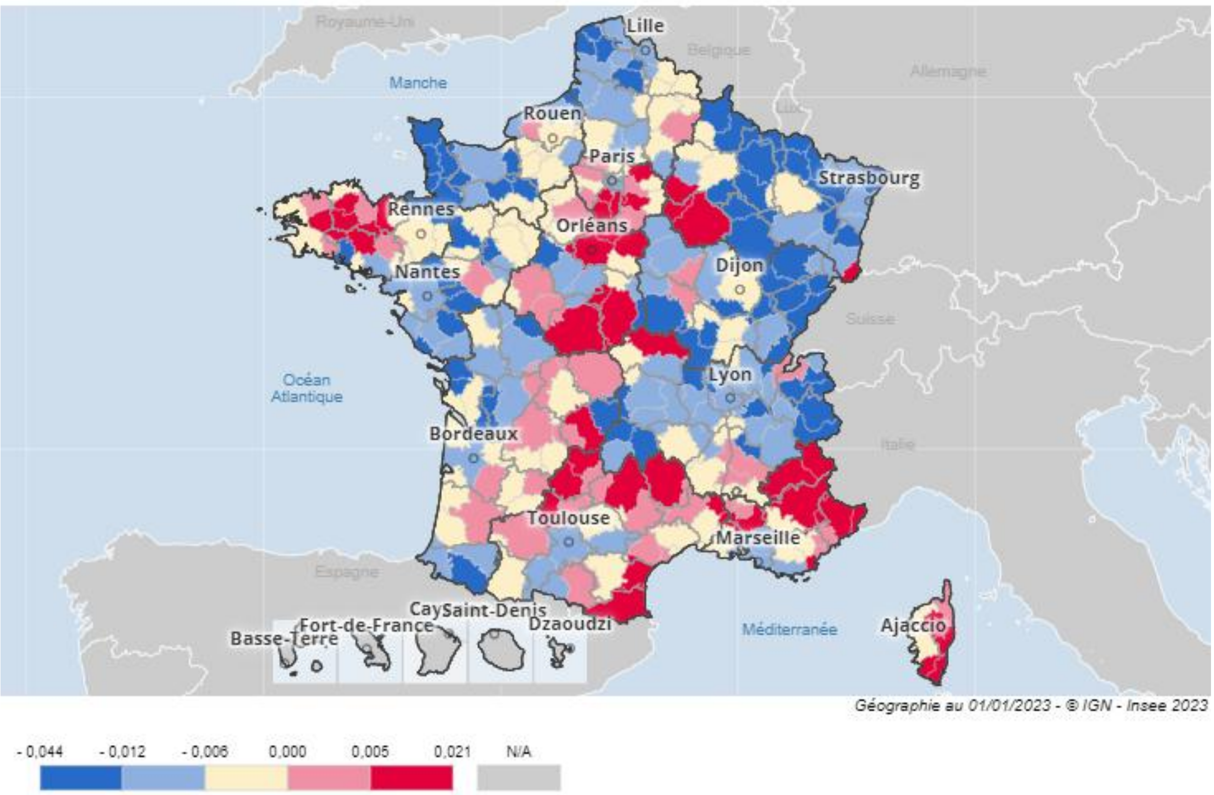
[9] See Kane (2022), Kane and Lopez (2023) for more details on the method.

indicator of the financial health of the geographical area, capable of encompassing both supply and demand characteristics. It constitutes what is known as the local propensity to generate wealth (Levratto & Garsaa, 2016). As in several previous studies (Ciccone & Hall, 1996; Levratto & Garsaa, 2016), we approximate agglomeration effects using the ratio given by the number of employees in the FCS, divided by its area measured in square kilometres, expressed in logarithm, *lndens*. Density characterises the role of an area's economic activity and enables us to assess external agglomeration effects.

We consider median income, expressed in logarithm *lnmedian_income*, to take into account the labour market area's wealth. This indicator is relevant because, on the one hand, it reflects household disposable income at the labour market area level, and, on the other, it can influence the level of local demand. Scott (1999) notes that the level of income within a region is likely to have significant implications for business competitiveness. Median income and the unemployment rate are usually linked. Herpin (1992) has already shown for France a negative correlation between the unemployment rate and the level of median income at the level of the employment zone, on the one hand, and a negative relationship between the unemployment rate and the level of demand, on the other.

Figures 1, 2 and 3 display the average growth of our three local variables across the labour market area between 2009 and 2019.[10] Looking at the maps, we notice that the dynamics of average growth rates differ significantly from area to area. The distribution of these three variables is highly heterogeneous across the employment zones.

Figure 1. Average growth in unemployment rate between 2009 and 2019



[10] The authors drew the maps using the Insee mapping tool.

Figure 2. Average growth in employment density between 2009 and 2019

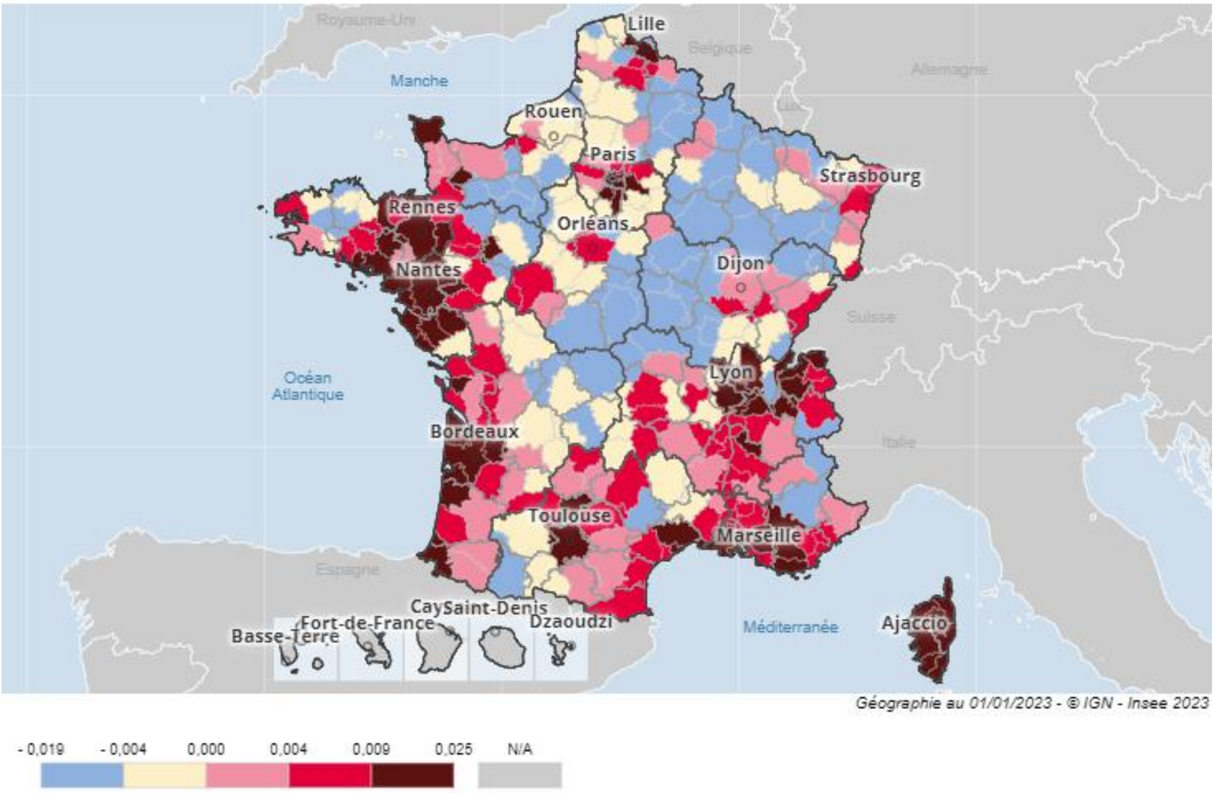
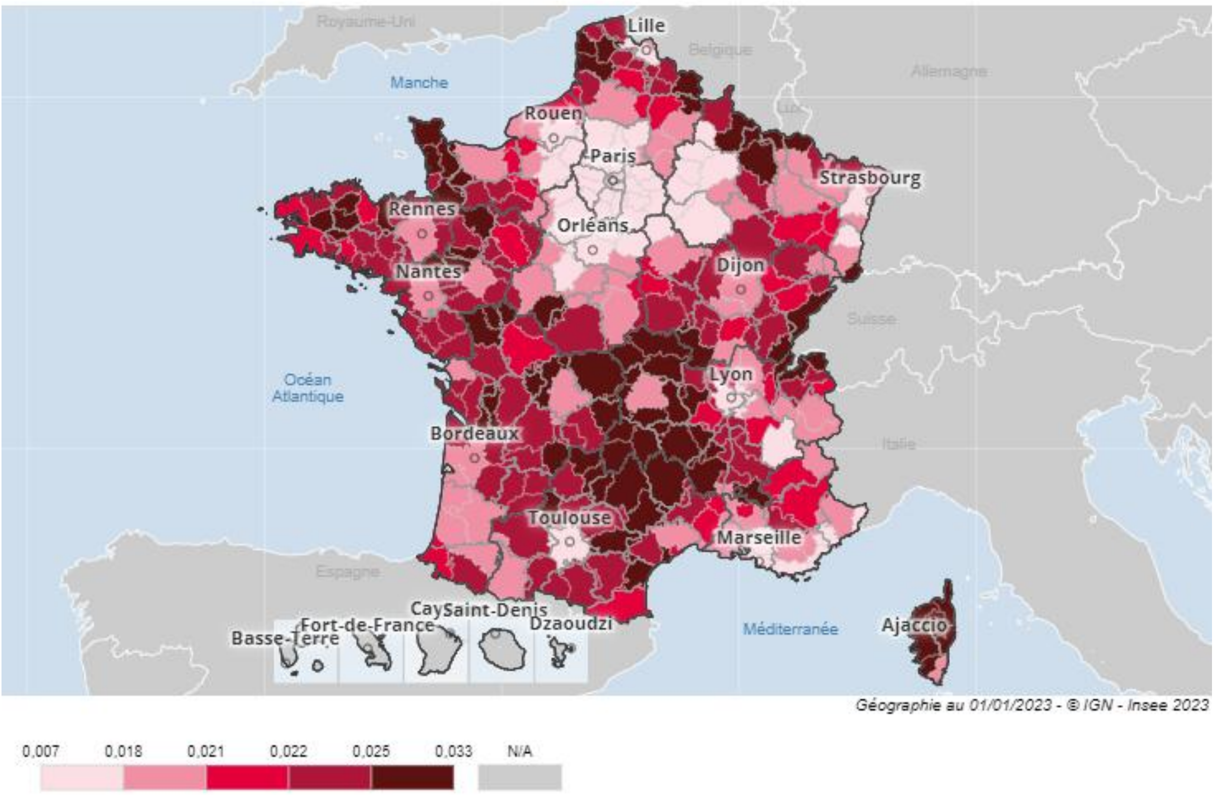


Figure 3. Average growth in median income between 2009 and 2019



Firm-level variables

The determinants of productivity defined at the firm level include size, age, share of executives and intermediate professions in the total workforce and financial liquidity variables such as operating subsidies and the company's self-financing capacity. Several empirical studies related to productivity show a positive effect of size on firm productivity (Van Ark & Monnikhof, 1996; Bartelsman et Doms, 2000; Baldwin et al., 2002). This result comes from the fact that larger firms are characterised by higher levels of profitability (Hurst & Pugsley, 2011; Fort et al., 2013) and consequently face less bankruptcy risk than small firms (Arcuri & Levratto, 2018). We also introduce the square of size into the model to consider a possible non-linear effect on firm performance at the local level (Raspe & van Oort, 2008). Following Coad (2009) and Fattah et al. (2020), we adopt an accounting conception of firm size and define this variable "*lnsize*'' by the logarithm of the annual turnover of a company.

The relationship between the age of a firm and its productivity has also been frequently investigated in the literature. Most studies show that productivity levels improve with firm age (Brouwer et al., 2005; Coad et al., 2013), although some authors have found contrary results (Jensen et al., 2001; Alon et al., 2018). We thus introduce it into the equation to be estimated. The variable "*lnage*'' is computed as the logarithmic difference between the current year and the year the company was founded. We also include the square of age in the model.

Theoretical models of human capital (Schultz, 1961 ; Becker 1964) and empirical (Mankiw et al., 1992; Engelbrecht, 1997; Crook et al., 2011) show that knowledge and skills directly increase productivity and the economy's ability to adopt new technologies. Based on this abundant literature, we introduce an approximation of human capital expressed as the share of executives and intermediate professions in the total workforce "*csp_plus*''.

In addition to the previous variables of interest, we introduce two financial variables to control for the firm robustness. First, the operating subsidies per turnover and the company's self-financing capacity are expressed in logarithm, "*self_capacity*''. Their sign is expected to be positive.

Table 1 provides the definitions and sources of the variables.

Table 1. Definitions and sources of variables

Name	**Definition**	**Source**
Dependent variable	Labour productivity and TFP	FARE
Explanatory variables		
Local variables		
unemp	Unemployment rate per labour market area	Insee
lndens	Logarithm of number of employees/labour market area (square kilometres)	Insee
lnmedian_income	Logarithm of median income in the labour market area	Insee
Firm variables		
lnsize	Logarithm of annual turnover	FARE

lnold	Logarithm (Current year - year of incorporation of the company)	FARE
csp_plus	Human capital represented by the average share of executives and intermediate professions in the total workforce	FARE
subsidies	The operating subsidies per turnover	FARE
self_capacity	The company's self-financing capacity in logarithm	FARE

Tables A1 and A2 in Appendix A present the descriptive statistics for the production and location variables, respectively. Table B of Appendix B presents estimation results using alternative methods (e.g. Fixed effects method; Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Wooldridge, 2009). They show that returns to scale are decreasing: output varies less than proportionally to the factors of production used. In addition, the estimated values of the elasticities of capital intensity and intermediate inputs are positive and highly significant. However, capital intensity elasticity is very low in the FCS. Kane (2022) and Kane & Lopez (2023) have already raised this distinctive aspect of the construction sector.

3.4 The model

Model description

Firm-level panel data is an example of a hierarchical structure, with repeated observations over time nested within firms that are also nested within geographic areas nested within geographic areas. Specifically, firms operate in a socioeconomic context that significantly affects their economic performance (Levratto & Garsaa, 2016; Fattah et al., 2020). Indeed, firms operating in the same territory share the same external environment; therefore, they are likely to be more similar than firms operating in different geographical areas. Thus, the underlying econometric problem will be the violation of the standard deviation independence assumption, leading to biased estimated coefficients. The multilevel approach circumvents this difficulty since it controls for spatial dependence and corrects for standard deviations of variables by modelling both fixed effects (the approach looks at means) and random effects (the approach looks at variances).

Multilevel models make it possible to avoid two types of error: (i) the ecological error, which consists of interpreting at the individual level the results of a model carried out at an aggregate level, and (ii) the atomistic error, which leads to ignoring the context in which the individual evolves and extending a set of individual effects to the dimension of the context. They thus make it possible to measure the compositional effects in the variability of the variable explained between the different groups formed by comparing the variance at the group level before and after the introduction of individual characteristics. They also make it possible to determine whether the intergroup variations identified concern all the individuals in the groups or only some of them. Finally, they allow us to measure whether contextual characteristics explain the intergroup variability. Level 1 coefficients (constants and/or slopes) can vary according to Level 2 units; this variation is itself modelled and explained by variables related to Level 2 units.

We use a three-level hierarchy to follow the literature on multilevel panel data models (Steele, 2008; Levratto & Garsaa, 2016; Aiello & Bonanno, 2018; Fattah et al., 2020). The temporal dimension represents level 1 of the model; the observed firms represent level 2 of the structure; as the firms operate in different French geographical areas, these represent level 3 of the hierarchy.

Multilevel equation

The basic specification of a multilevel model can be expressed as follows:

$$y_{tij} = \beta_{0ij} + e_{tij} \tag{4}$$

where y_{tij} is a vector of the productivity measure of the *i-th* firm operating in the *j-th* geographic area at time *t* (with *t = 2009, ..., 2019*; *i = 1, ..., 78,598* and *j = 1, ..., p*). The error term is equivalent to e_{tij}.

Since the β_{0ij} term varies across firms and geographic areas, it is decomposed into a constant γ_{000} and random variations at the firm level μ_{0ij} and the geography level μ_{00j}. Equation (4) then becomes:

$$y_{tij} = \gamma_{000} + \mu_{0ij} + \mu_{00j} + e_{tij} \tag{5}$$

When equation (5) contains no explanatory variables, it is called an empty model. The augmented multilevel model is obtained by including explanatory variables at the firm level (X_{ktij}, where *k* is the number of covariates) and at the geographic level (G_{htij}, where *h* is the number of local covariates) in the empty model. Thus, the final econometric specification becomes:

$$y_{tij} = \gamma_{000} + \sum_{k=1}^{r} \beta_k X_{ktij} + \sum_{h=1}^{s} \theta_h G_{htij} + \mu_{0ij} + \mu_{00j} + e_{tij} \tag{6}$$

From equation (6), we decompose the variance of the explained variable (y_{tij}) into three components: the variance of the error term e_{tij}, which is equivalent to the within-group variance (σ_e^2), the variance of μ_{00j}, which refers to the between-group variance of geographic areas ($\sigma_{\mu j}^2$), and the variance of μ_{0ij}, corresponding to the between-group variance at the firm level ($\sigma_{\mu i}^2$).

From these variances, we calculate the intra-class correlation (ICC). It represents the proportion of the underlying variance at each level of the model hierarchy and explains how the heterogeneity of the dependent variable can be attributed to each level. The intra-class correlation at a given level is calculated as the ratio of the variance at that level to the total variance:

$$ICC_i = \frac{\sigma_{\mu i}^2}{\sigma_{\mu j}^2 + \sigma_{\mu i}^2 + \sigma_e^2} \quad \text{at firm-level}$$

$$ICC_j = \frac{\sigma^2_{\mu j}}{\sigma^2_{\mu j}+\sigma^2_{\mu i}+\sigma^2_e} \qquad \text{at location level}$$

$$ICC_t = \frac{\sigma^2_{e}}{\sigma^2_{\mu j}+\sigma^2_{\mu i}+\sigma^2_e} \qquad \text{at temporal level}$$

4 Results

4.1 Empty models

This section presents the origin of heterogeneity in productivity using the multilevel method, which incorporates unobserved heterogeneity into the model by considering the hierarchical structure of the data. Tables 2 and 3 show the results of the empty models for labour productivity and TFP, respectively, at the level of the 287 French metropolitan employment zones in 2020. Column 1 refers to Table 4 (augmented model) refers to labour productivity "*lnlp*'', while column 2 refers to TFP "*lntfp*''. In the augmented model (Table 4), we have introduced sub-sector fixed effects. The likelihood ratio test for the empty models is significantly different from zero, confirming the relevance of the multilevel model.

Our results underline that location matters and productivity levels depend on the local context. Column (1) of Tables 2 and 3 refers to the random intercept empty model in which the second level is formed by 80,986 firms and the third level is composed of 287 labour market areas. The value of the ICC represents the proportion of variability underlying each level of the model hierarchy: unaccounted labour market area-specific features capture (21.75% for LP and 18.13% for TFP) of firm productivity, time-specific factors explain (42.91% for LP and 32.31% for TFP) of variability, and the remaining (35.34% for LP and 49.56% for TFP) is attributable to firm-specific features. The high proportion of heterogeneity explained by the labour market area level confirms hypothesis 1 (H1), stating that coherent with the heterogeneity-performance approach, combining individual and local-level factors explains firm productivity more accurately than individual characteristics alone.

Column (2) of Tables 2 and 3 shows the results obtained when we augment the empty model with the variable "*year*''. In this case, the temporal variable is included in the deterministic part of the model to explain the company's productivity. This variable has a negative sign and is significant at the 1% level, showing that the productivity of FCS firms decreases with time. This finding shows that the economic performance of the FCS is sensitive to exogenous factors linked to temporal fluctuations. This specification shows almost similar percentages to those in column 1 of Tables 4 and 5 to explain the heterogeneity in productivity due to unobservable location-specific factors (21.70% for LP and 17.91% for TFP).

Column (3) of Tables 2 and 3 shows the results for the empty model obtained adding time as a source of productivity in employment zone intercepts and slopes. We test this type of specification because different employment zones may react differently to global shocks depending on the characteristics of the productive system.[11] In order to select the best-performing regression, we display the Akaike Information Criterion (AIC) for the empty model. The results show that model (3), in which we consider the time intercept and random slopes at

[11] We do not show the result of the ICC for model (3) since in models with random slopes, the variance of the slope (and, as a consequence, the covariance) is related to the values of the explanatory variable for which the random slope is specified (*Time*). Thus, the ICC is no longer uniquely defined.

the labour market area level (level 3), presents the best performance (the lowest AIC value). We, therefore, retain this specification for the next stage, in which we augment the multilevel model with a set of factors specific to the company and the employment zone (Table 4).

Table 2. Empty models for labour productivity

	(1) **No time effect**	**(2)** **Time intercept effect**	**(3)** **Time intercept and random slope at the level 3**
Constant	-0.560***	17.063***	17.077***
	(0.001)	(0.366)	(0.366)
year		-0.009***	-0.009***
		(0.0002)	(0.0002)
Variance			
Firm	0.098	0.10	0.099
Labour market area (intercept)	0.060	0.060	3.6^{e}-11
Labour market area (slope)			1.518^{e}-08
Residual	0.119	0.118	0.118
ICC (%)			
Labour market area	21.75	21.70	
Firm	35.34	35.96	
Time	42.91	42.34	
Number of observations	533,258	533,258	533, k258
Number of groups			
Firm level	78,598	78,598	78,598
Labour market area level	287	287	287
Log likelihood	-277 153.31	-276 000.22	-275 987.49
LR test	2.3e+05***	2.3e+05***	2.3e+05***
AIC	554 314.6	552 014.4	551 987

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3. Empty models for total factor productivity

	(1) **No time effect**	**(2)** **Time intercept effect**	**(3)** **Time intercept and random slope at the level 3**
Constant	4.045***	9.819***	9.850***
	(0.001)	(0.112)	(0.112)
year		-0.003***	-0.003***
		(0.0001)	(0.0001)
Variance			
Firm	0.017	0.017	0.017
Labour market area (intercept)	0.006	0.006	0.006
Labour market area (slope)			3.969^{e}-17
Residual	0.011	0.011	0.011
ICC (%)			

Labour market area	18.13	17.91	
Firm	49.56	50.06	
Time	32.31	32.03	
Number of observations	533,258	533,258	533,258
Number of groups			
Firm level	78,598	78,598	78,598
Labour market area level	287	287	287
Log likelihood	346 032.86	347 363.86	347 363.86
LR test	3.3e+05***	3.4e+05***	3.4e+05***
AIC	-692 057.7	-694 717.7	-694 717.7

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.2 Augmented models

The effect of level 3 variables (unemployment rate, employment density and local wealth) on productivity is consistent with expectations. The level of productivity is negatively correlated with the local unemployment rate "*unemp*''. Our second hypothesis, H2, is valid. Considered as an indicator of demand, the negative sign associated with the unemployment rate confirms the Keynesian relationship between employment and demand for consumer goods. A drop in local demand resulting from a reduction in the level of employment following a downward adjustment in the production level of construction companies located in the same area tends to discourage productivity in the sector. This result is similar to Levratto and Garsaa (2016) for industrial companies.

Employment density "*lndens*'' positively affects the level of productivity in French construction, which is consistent with our third hypothesis, H3. Agglomeration externalities, therefore, stimulate the economic performance of companies in the sector. These agglomeration economies are mainly the result of the shared resources available to companies located in the same area. In a denser and larger local market, a firm can obtain a greater variety of intermediate inputs and generate productivity gains through higher levels of vertical disintegration and specialisation (Henderson, 2003). The availability of a greater variety of consumer goods also attracts consumers and, consequently, increases the level of demand. In the case of increasing returns, companies benefit from larger market. Our results are consistent with the literature (Ciccone & Hall, 1996; Levratto & Garsaa, 2016).

The median income of the labour market area has a significant and positive effect on the TFP of FCS companies, thus confirming H4. The literature shows a positive relationship between productivity and area endowment, which implies that agglomeration economies specific to cities affect productive efficiency. Indeed, higher median incomes in a labour market area often correlate with a more educated and skilled workforce. In the construction sector, an increase in the education levels of workers can positively impact productivity. For instance, the UK's Office for National Statistics notes that while education might not be a perfect measure of worker skill in construction, where on-the-job training is crucial, the relative increase in education levels could still positively affect productivity (Office for National Statistics, 2021). Higher median incomes can also indicate a more affluent and technologically advanced region. This can lead to greater investment in technology and innovation, which is critical for improving TFP. For example, the analysis of the European construction sector shows that regions with higher median incomes might be more likely to invest in such advancements (Bellochi & Tavaglini, 2023).

Table 4 also presents the results obtained using level 2 variables. The effect of age “*lnage*’’ on productivity (LP and TFP) is strictly decreasing, meaning that firm productivity decreases with age. The decreasing relationship between the age of companies and their productivity is not a surprise if we consider the size of companies in the construction sector in France. The FCS is composed mainly of micro-businesses. In 2021, 95.1% of companies in this sector were micro-businesses (Insee, Ésane 2021), mainly young companies. Our result confirms Coad et al. (2013), who also found that the performance of Spanish manufacturing firms deteriorated with age between 1998 and 2006. The authors showed that, when other variables such as size are taken into account in the analysis, older firms have lower expected growth rates for sales, profits and productivity, they have lower levels of profitability, and they also appear less able to convert employment growth into growth in sales, profits and productivity.

We find a statistically significant inverted U-shaped relationship between company size “*lnsize*’’ and productivity. As a company grows, its productivity increases to a certain threshold and then decreases. This non-linear relationship has an economic explanation. Indeed, some studies show that the size of a company contributes to its performance when it is in the development phase. However, when the company grows, the relationship between size and performance can be negative (Hung et al., 2019).

Our estimates also show a positive and significant relationship between human capital and productivity. The proportion of executives and the proportion of intermediate professions “*csp_plus*’’ have a positive and significant effect on the productivity of FCS companies. Executives in the construction sector are technically and often financially responsible for or involved in managing one or more construction sites. They are also responsible for coordinating the allocation of resources to the various sites according to the work's progress and ensuring that deadlines are met. As such, they are highly qualified and often experienced, which increases their productivity. This result is in line with the literature. Kordalska and Olczyk (2020) find a significant and positive relationship between labour productivity and the proportion of employees with a university degree (workers' skills) in Eastern Europe and Central Asia countries. Zhi et al (2003) provide evidence of a significant and negative effect of the proportion of foreign (unskilled) workers on TFP growth in Singapore construction firms between 1984 and 1998.

The control variables introduced into the equation to be estimated enable us to refine our analysis. The relationship between the company's self-financing capacity and its productivity level is positive. This result is intuitive since a company's self-financing capacity represents the gross resources remaining at the end of the financial year, which are then either distributed or reserved to finance its investments. Consequently, any increase in this indicator leads to an increase in the firm's productivity and can also predict future productivity (Fairfield & Yohn, 2001). In contrast, the link between operating subsidies per turnover and productivity is mixed, depending on the type of productivity. We have a significant negative effect on LP and a positive effect on TFP. Our findings can be generalised to other sectors such as manufacturing (Aiello & Ricotta, 2016 and Amara & Thabet, 2019).

Table 4. Model with firm and labour market area-specific variables

Variables	(1) **lnlp**	(2) **lntfp**
unemp	-0.0129***	-0.00558***
	(0.000470)	(0.000165)
lndens	0.0123***	0.00685***
	(0.000964)	(0.000366)
lnmedian_income	-0.0117	0.0769***
	(0.0127)	(0.00459)
lnage	-0.0184***	-0.0125***
	(0.00222)	(0.000745)
ln²age	-0.0111***	-0.00199***
	(0.000634)	(0.000226)
lnsize	0.287***	0.0547***
	(0.00615)	(0.00219)
ln²size	-0.0192***	-0.00386***
	(0.000434)	(0.000155)
csp_plus	0.00950***	0.00210***
	(0.00152)	(0.000494)
subsidies	-1.659***	0.552***
	(0.0773)	(0.0257)
self_capacity	0.122***	0.0427***
	(0.000563)	(0.000185)
year	-0.00680***	-0.00309***
	(0.000290)	(0.000104)
Constant	12.12***	9.236***
	(0.491)	(0.176)
Variance		
Firm	0.008	0.015
Labour market area (intercept)	6.150e-10	0.004
Labour market area (slope)	8.742e-09	1.102e-17
Residual	0.065	0.007
Number of observations	446,593	446,593
Number of groups		
Firm level	78,598	78,598
Labour market area level	287	287
Log likelihood	-113 217.94	376 138.46
LR test	2.2e+05***	3.1e+05***
Sub-sector FE	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The following sub-section will check the robustness of our estimation results by opting for a much finer geographical grid.

4.3 Robustness check

We complete our analysis of the influence of the location context on company productivity by considering the firm size. Table 5 provides the robustness results when we use the classification by firm size. Columns 1 and 2 refer to micro-enterprises (less than 20 employees), columns 3 and 4 to small enterprises (between 20 and 99 employees) and columns 5 and 6 to medium and large enterprises (100 or more employees). The two dependent variables remain unchanged: LP and TFP.

Table 5 confirms the robustness of our local effects on FCS productivity. The sign of the unemployment rate remains significant and negative, whereas the signs of employment density and median income are significant and positive regardless of firm size. We confirm the Keynesian relationship between employment and demand and the effects of positive external agglomeration. Location-specific characteristics remain crucial in explaining productivity differences between firms in the sector. Likelihood ratio tests confirm the interest of the multilevel model independently of the dependent variable.

The effect of firm-specific variables, notably age and firm size, is sensitive to size classification. We find the same relationships as in Table 4 for micro-enterprises. The interpretation of the relationships between the explanatory variables and our dependent variables at the micro-enterprise level is similar to that of the total sample. We find a statistically significant U-shaped relationship between firm age and productivity for small companies (between 20 and 99 employees). In contrast, the relationship takes the inverted U-shaped for medium-sized and large companies (100 or more employees). This contrast is much more evident in terms of LP. For small companies, this non-linear result means that the performance of small businesses initially suffers from a novelty liability, before increasing as a result of maturity and learning effects (Coad et al., 2018). Similar results have been confirmed, for example, by Brouwer et al. (2005) for Dutch manufacturing industries, by Alon et al. (2018) for US non-agricultural industries, and by Dvouletý & Blažková (2021) for Czech companies.

Table 5 shows again a statistically significant inverted U-shaped relationship between age and productivity for medium-sized and large firms. This impact is also found in the literature. Coad et al. (2013) note that age influences firm performance in three ways (selection, learning-by-doing, and inertia effects), depending on whether firm performance remains the same, improves or declines over time. Kordalska and Olczyk (2020) made the same observation based on Eastern Europe and Central Asia countries. They note that during the company's first period of activity, its productivity is sustained by growing experience and the effect of 'learning by doing'. However, as the company ages, its productivity decreases due to increased inertia and flexibility. The inverted U-shaped relationship between firm size “*lnsize*’’ and productivity remains strong, except for the TFP of small firms where we have a U-shaped relationship.

The proportion of executives and the proportion of intermediate professions, the company's self-financing capacity and operating subsidies per turnover show signs similar to those of the global sample (Table 4). These variables are, therefore, robust, even though the variable “*csp_plus*’’ does not affect the productivity of medium and large companies.

Table 5. Robustness model

Company size	Micro		Small		Medium and Big	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**lnlp**	**lntfp**	**lnlp**	**lntfp**	**lnlp**	**lntfp**
unemp	-0.0132***	-0.00560***	-0.00666***	-0.00387***	-0.0183***	-0.00533***
	(0.000515)	(0.000182)	(0.000702)	(0.000316)	(0.00211)	(0.000817)
lndens	0.0103***	0.00622***	0.0257***	0.0129***	0.0257***	0.0101***
	(0.00104)	(0.000397)	(0.00155)	(0.000721)	(0.00394)	(0.00152)
lnmedian_income	-0.0174	0.0804***	-0.0551	0.0544***	-0.0629	0.0686***
	(0.0138)	(0.00504)	(0.0195)	(0.00885)	(0.0547)	(0.0210)
lnage	-0.0251***	-0.0133***	-0.0247***	-0.0176***	0.0606***	-0.00618
	(0.00239)	(0.000803)	(0.00660)	(0.00295)	(0.0209)	(0.00813)
ln²age	-0.00763***	-0.00109***	0.00451***	5.12e-05	-0.0125***	-0.00295*
	(0.000698)	(0.000248)	(0.00138)	(0.000629)	(0.00414)	(0.00164)
lnsize	0.143***	0.0462***	0.911***	-0.196***	0.967***	0.0125
	(0.00969)	(0.00334)	(0.0283)	(0.0126)	(0.0728)	(0.0287)
ln²size	-0.00626***	-0.00299***	-0.0407***	0.0122***	-0.0416***	-6.75e-05
	(0.000740)	(0.000254)	(0.00162)	(0.000724)	(0.00329)	(0.00130)
csp_plus	0.0111***	0.00243***	0.00156	0.00132*	0.00462	0.000854
	(0.00185)	(0.000602)	(0.00158)	(0.000689)	(0.00365)	(0.00140)
subsidies	-1.768***	0.551***	0.244	0.739***	0.265	0.191*
	(0.0823)	(0.0273)	(0.196)	(0.0896)	(0.253)	(0.102)
self_capacity	0.127***	0.0450***	0.0827***	0.0289***	0.0737***	0.0235***
	(0.000633)	(0.000209)	(0.000777)	(0.000341)	(0.00222)	(0.000852)
year	-0.00742***	-0.00371***	-0.0152***	-0.00273***	-0.0101***	-0.000168
	(0.000324)	(0.000118)	(0.000422)	(0.000192)	(0.00109)	(0.000424)
Constant	13.83***	10.45***	25.52***	9.682***	14.56***	3.524***
	(0.555)	(0.200)	(0.720)	(0.326)	(1.836)	(0.715)

Variance						
Firm	0.08	0.016	0.03	0.008	0.036	0.007
Labour market area (intercept)	9.025e-13	0.004	3.576e-13	0.001	2.853e-08	0.0003
Labour market area (slope)	8.761e-09	2.209e-19	2.746e-09	2.28e-16	1.19e-09	6.593e-17
Residual	0.069	0.007	0.015	0.0029	0.013	0.0019
Number of observations	386,408	386,408	54,199	54,199	5,986	5,986
Number of groups						
Firm level	72,981	72,981	10,135	10,135	984	984
Labour market area level	287	287	287	287	287	287
Log likelihood	-112,433.19	309,602.96	23,125.036	67,156.613	3,050.5167	8,734.4341
LR test	1.8e+05***	2.7e+05***	36,473,9***	41,767.78***	4,573.92***	4,688.46***
Sub-sector FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.5, * p<0.1

5 Conclusion

This paper investigates the productivity heterogeneity among French construction firms using the FARE database, which encompasses 78,598 firms in mainland France between 2009 and 2019. By employing a multilevel model, the study identifies two principal findings.

First, the analysis highlights the significant role of location-specific factors in explaining productivity heterogeneity. At the labour market area level, these factors account for 21.75% of the variability in labour productivity and 18.13% in total factor productivity (TFP). Among the location-specific variables considered, the local unemployment rate negatively affects firm productivity, as reduced demand and employment in the construction sector diminish performance. In contrast, employment density generates positive agglomeration effects, with shared resources among firms in the same area fostering productivity. Furthermore, median income within an employment zone positively influences TFP, underscoring the importance of local wealth in enhancing firm competitiveness. These findings emphasise the critical impact of regional economic conditions on firm performance.

Second, firm-specific factors emerge as the most significant determinants of productivity, explaining 35.34% and 49.56% of the variability in labour productivity and TFP, respectively. The study identifies several relevant firm-specific variables. Firm age exhibits a consistently negative relationship with productivity among micro-businesses. In contrast, small firms display a U-shaped relationship, and medium-to-large firms exhibit an inverted U-shaped pattern. This suggests that experience may improve productivity over time for smaller firms, whereas larger firms face challenges related to inertia and flexibility. Firm size also demonstrates a non-linear relationship with productivity; while growth initially enhances performance, excessive size can reduce efficiency. Human capital, measured by the proportion of executives and intermediate professions in the workforce, consistently enhances productivity across all firm sizes. Financial indicators, such as operating subsidies and self-financing capacity, also positively influence productivity, although subsidies harm labour productivity in micro-businesses.

Our findings suggest several policy recommendations regarding government support for this industry. Given the significant impact of local conditions on firms' productivity, policymakers should consider measures to boost demand through public spending in response to a local shock, thereby mitigating the crisis's effects on firms. Furthermore, our results can inform firms' strategies by encouraging companies to pursue growth initiatives that enable their businesses to thrive independently of local circumstances.

While the multilevel modelling approach effectively accounts for the influence of local context and firm-specific factors, its limitations include the inability to fully capture the interdependence of productivity determinants and the presence of latent variables. These limitations may lead to underestimating location effects, as the identified net effects reflect joint, rather than absolute, impacts. Another issue, not addressed in the paper, is the potential problem of endogeneity. Although they are two completely different variables, the unemployment rate and employment density may explain the same phenomenon. Despite these constraints, the approach demonstrates considerable potential for analysing spatial disparities in firm performance and growth trajectories. Future research would benefit from access to localised data at finer spatial scales to more precisely capture the nuances of regional economic conditions.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. Econometrica, 83(6):2411–2451.

Aiello, F. and Bonanno, G. (2018). Multilevel empirics for small banks in local markets. Papers in Regional Science, 97(4):1017–1037.

Aiello, F. and Ricotta, F. (2016). Firm heterogeneity in productivity across Europe: evidence from multilevel models. Economics of Innovation and New Technology, 25(1):57–89.

Aiello, F., Pupo, V., and Ricotta, F. (2014). Explaining total factor productivity at firm level in Italy: Does location matter? Spatial Economic Analysis, 9(1):51–70.

Alon, T., Berger, D., Dent, R., and Pugsley, B. (2018). Older and slower: The startup deficit's lasting effects on aggregate productivity growth. Journal of Monetary Economics, 93:68–85.

Amara, M. and Thabet, K. (2019). Firm and regional factors of productivity: a multilevel analysis of Tunisian manufacturing. The Annals of Regional Science, 63(1):25–51.

Andersson, M., Lööf, H. (2011). Agglomeration and productivity: evidence from firm-level data. Annals of Regional Science, 46, 601–620. https://doi.org/10.1007/s00168-009-0352-1

Arcuri, G., & Levratto, N. (2018). Early stage SME bankruptcy: Does the local banking market matter? Small Business Economics, 54, 421–436. https://doi.org/10.1007/s11187-018-0042-4.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. The American economic review, 86(3), 630-640.

Baldwin, J. R., Jarmin, R. S., & Tang, J. (2002). The trend to smaller producers in manufacturing: A Canada/US comparison. *Statistics Canada, Analytical Studies-Economic Analysis, Series 1F0027MIE*, (003).

Baldwin, R. E. and Okubo, T. (2006). Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting. Journal of economic geography, 6(3):323–346.

Barnichon, R. (2010) Productivity and unemployment over the business cycle. Journal of Monetary Economics, 57(8): 1013-1025

Barrett, P., Chen, S. Lin, L. & Weber, A. (2024). The Dynamic Effects of Local Labor Market Shocks on Small Firms in The United States. IMF Working paper, March, WP/24/63. Available on-line: https://www.imf.org/-/media/Files/Publications/WP/2024/English/wpiea2024063-print-pdf.ashx

Bartelsman, E. J. and Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. Journal of Economic literature, 38(3):569–594.

Becker, G. S. (1964). Human capital: A theoretical and empirical analysis with special reference to education. National Bureau of Economic Research.

Bellocchi, A., & Travaglini, G. (2023). A quantitative analysis of the European construction sector: productivity, investment, and competitiveness. In *Digital Transitions and Innovation in Construction Value Chains* (pp. 18-48). Edward Elgar Publishing.

Brouwer, P., De Kok, J., and Fris, P. (2005). Can firm age account for productivity differences. EIM SCALES-paper N, 200421:1–49.

Caves, R. E. (1998). Industrial organisation and new findings on the turnover and mobility of firms. Journal of economic literature, 36(4):1947–1982.

CICCONE, A. and HALL, R. (1996). Productivity and the Density of Economic activity. American Economic Review, 86 (1), 54-70.

Coad, A. (2009). The growth of firms: A survey of theories and empirical evidence. Cheltenham: Edward Elgar.

Coad, A., Holm, J.R., Krafft, J. *et al.* Firm age and performance. *J Evol Econ* **28**, 1–11 (2018). https://doi.org/10.1007/s00191-017-0532-6.

Coad, A., Segarra, A., and Teruel, M. (2013). Like milk or wine: Does firm performance improve with age? Structural Change and Economic Dynamics, 24:173–189.

Criscuolo, C., Hijzen, A., Koelle, M., Schwellnus, C., Barth, E., Chen, W. H., ... & Zwysen, W. (2021). The firm-level link between productivity dispersion and wage inequality: A symptom of low job mobility? Documents de travail de l'OCDE sur la science, la technologie et l'industrie, n° 2021/02, Éditions OCDE, Paris, https://doi.org/10.1787/882a4055-en

Crook, T. R., Todd, S. Y., Combs, J. G., Woehr, D. J., and Ketchen Jr, D. J. (2011). Does human capital matter? A meta-analysis of the relationship between human capital and firm performance. Journal of applied psychology, 96(3):443.

Dvouletý, O., & Blažková, I. (2021). Exploring firm-level and sectoral variation in total factor productivity (TFP). International Journal of Entrepreneurial Behavior & Research, 27(6), 1526-1547.

Engelbrecht, H.-J. (1997). International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation. European Economic Review, 41(8):1479–1488.

Ericson, R. and Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. The Review of economic studies, 62(1):53–82.

Faggio, G., Salvanes, K. G., & Van Reenen, J. (2010). The evolution of inequality in productivity and wages: panel data evidence. *Industrial and Corporate Change*, *19*(6), 1919-1951.

Fairfield, P. M. and Yohn, T. L. (2001). Using asset turnover and profit margin to forecast changes in profitability. Review of accounting Studies, 6(4):371–385.

Farinas, J. C. and Ruano, S. (2005). Firm productivity, heterogeneity, sunk costs and market selection. International Journal of Industrial Organization, 23(7-8):505–534.

Fattah, L. A., Arcuri, G., Garsaa, A., & Levratto, N. (2020). Firm financial soundness and knowledge externalities: A comparative regional analysis. *Papers in Regional Science*, *99*(5), 1459-1487.

Fazio, G. and Piacentino, D. (2010). A spatial multilevel analysis of Italian SMEs'productivity. Spatial Economic Analysis, 5(3):299–316.

Fort, T., Haltiwanger, J., Jarmin, R., & Miranda, J. (2013). How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size. IMF Economic Review, 61, 520–559.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In New developments in productivity analysis, pages 303–372. University of Chicago Press.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. Journal of political economy, 100(6), 1126-1152.

Haltiwanger, J. (2000). Aggregate growth: what have we learned from microeconomic evidence? OECD Publishing.

Henderson, J. V. (2003). Marshall's scale economies. Journal of Urban Economics, 53(1), 1–28. https://doi.org/10.1016/S0094-1190(02)00505-3

Herpin, N. (1992). Les conséquences du chômage sur la consommation. Economie et Statistique (256), 43-57.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. Econometrica: Journal of the Econometric Society, pages 1127–1150.

Hung, S. W., Li, C. M., & Shen, M. Y. (2019). Does a U-shaped relationship exist between performance and size threshold?: The evidence from Taiwan biotech industry. Technology in Society, 58, 101147.

Hurst, E., & Pugsley, B. W. (2011). What Do Small Businesses Do? NBER Working Paper No. w17041. Available at SSRN: https://ssrn.com/abstract=1841278.

Jensen, J. B., McGuckin, R. H., and Stiroh, K. J. (2001). The impact of vintage and survival on productivity: Evidence from cohorts of US manufacturing plants. Review of Economics and Statistics, 83(2):323–332.

Jovanovic, B. (1982). Selection and the evolution of industry. Econometrica: Journal of the econometric society, pages 649–670.

Kané, A. (2022). Measurement of total factor productivity: Evidence from French construction firms. EconomiX Working Papers, (2022-9).

Kane, A., & Lopez, J. (2023). Productivity and regulation in the construction sector: evidence for OECD countries. Applied Economics, 1-17.

Kordalska, A. and Olczyk, M. (2020). What fosters firm-level labour productivity in Eastern European and Central Asian countries? Bank i Kredyt, 51:91–120.

Krugman, P. (1991). Increasing returns and economic geography. Journal of political economy, 99(3):483–499.

Lavoratori, K., and Castellani, D. (2021) Too close for comfort? Microgeography of agglomeration economies in the United Kingdom. Journal of Regional Science, 61(5): 1002-1028. https://doi.org/10.1111/jors.12531

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. The review of economic studies, 70(2):317–341.

Levratto, N. and Garsaa, A. (2016). Does the employment growth rate depend on the local context? an analysis of French industrial establishments over the 2004-2010 period. Revue d'économie industrielle, (153):47–89.

Malecki, E. J. (1985). Industrial location and corporate organisation in high technology industries. Economic Geography, 61(4), 345-369.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. The quarterly journal of economics, 107(2):407–437.

Marshall, A. (1920). Principles of Economics. London: Macmillan and Co., Ltd.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. econometrica, 71(6):1695–1725.

Melitz, M. J. and Ottaviano, G. I. (2008). Market size, trade, and productivity. The review of economic studies, 75(1):295–316.

Melo P, Graham DJ and Noland RB (2009). A meta-analysis of estimates of urban agglomeration economies, Regional Science and Urban Economics 39, 332–342

Office for National Statistics (ONS) (2021) Productivity in the construction industry, UK: 2021. Available on-line : https://backup.ons.gov.uk/wp-content/uploads/sites/3/2021/10/Productivity-in-the-construction-industry-UK-2021.pdf

Olley, G. S. and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica, 64(6):1263–1297.

Raspe, O. and van Oort, F. G. (2011). Firm heterogeneity, productivity and spatially bounded knowledge externalities. Socio-Economic Planning Sciences, 45(1):38–47.

Raspe, O., & van Oort, F. (2008). Firm growth and localised knowledge externalities. The Journal of Regional Analysis and Policy, 38(2), 100–116.

Rosenthal, S. S. and Strange, W. C. (2003). Geography, industrial organisation, and agglomeration. Review of Economics and Statistics, 85(2), 377-393.

Schreyer, P., & Pilat, D. (2001). Measuring productivity. OECD Economic studies, 33(2), 127-170.

Schultz, T. W. (1961). Investment in human capital. The American economic review, 51(1):1–17.

Scott, A. J. (1999). Regions and the world economy: the coming shape of global production, competition, and political order. Oxford University Press.

Steele, F. (2008). Multilevel models for longitudinal data. Journal of the Royal Statistical Society: series A (statistics in society), 171(1):5–19.

Van Ark, B. and Monnikhof, E. (1996). Size distribution of output and employment: a data set for manufacturing industries in five OECD countries, 1960s-1990. Documents de travail du Département des Affaires économiques de l'OCDE.

Van Beveren, I. (2012). Total factor productivity estimation: A practical review. Journal of economic surveys, 26(1):98–128.

Weisskopf, T. E. (1987). The effect of unemployment on labour productivity: an international comparative analysis. International Review of Applied Economics, 1(2), 127–151. https://doi.org/10.1080/758528894.

Wooldridge, J. M. 2009. "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables." *Economics Letters* 104 (3): 112–114. doi:10.1016/j.econlet.2009.04.026.

Zhi, M., Hua, G. B., Wang, S. Q., and Ofori, G. (2003). Total factor productivity growth accounting in the construction industry of Singapore. Construction management and economics, 21(7):707–718.

Appendices

Appendix A – Variables descriptive statistics

Table A1. Descriptive statistics on production data

Variables	N	Mean	Sd	Min	Max
Real output per worker (€×1,000)	533,258	1.845	2.497	0.003	547.104
Real output per worker (in log)	533,258	0.402	0.579	-5.72	6.305
Real added value per worker (€×1,000)	533,258	0.666	0.748	0	341.161
Real added value per worker (in log)	533,258	-.0545	0.503	-8.248	5.832
Employment	533,258	15.006	85.65	1	6332
Employment (in log)	533,258	1.755	1.151	0	8.753
Real investment per worker (€×1,000)	533,258	0.068	0.801	7.10e-06	428.356
Real investment per worker (in log)	533,258	-3.826	1.529	-11.856	6.06
Capital intensity (€×1,000)	533,258	0.437	3.71	0	1023.593
Capital intensity (in log)	533,258	-1.493	1.073	-9.157	6.931
Real intermediate inputs per worker (€×1,000)	533,258	0.012	0.02	0	4.143
Real intermediate inputs per worker (in log)	533,258	-4.772	0.735	-10.922	1.421

Table A2. Description of local variables

Variables	N	Mean	Sd	Min	Max
$unemp$	533,258	9.133	1.99	4.3	18.1
$lndens$	533,258	3.832	1.571	0.379	8.405
$lnmedian\_income$	533,258	9.947	0.122	9.566	10.422

Note: *lndens*, *unemp* and *lnmedian_income* are respectively the unemployment rate, the logarithm of employment density and the logarithm of median income at employment zone level.

Appendix B – Estimation of the production function

Table B shows the results of estimating equation (*1*) using several semi-parametric methods.

Table B. Estimation of the production function

Dependent variable: *Production per employee (in log)*	(1) FE	(2) OP	(3) LP	(4) WRDG	(5) ACF
Labor input (γ, the return to scale)	-0.0504***	-0.0275***	-0.0260***	-0.0227***	-0.0273**
	(0.00123)	(0.000166)	(0.000172)	(0.000168)	(4.47e-06)
Capital intensity in log (β_k)	0.0559***	0.0769***	0.0675***	0.0781***	0.0388***
	(0.000933)	(0.00121)	(0.00137)	(0.000621)	(4.45e-06)
Intermediate input intensity in log (β_m)	0.784***	0.735***	0.743***	0.717***	0.742***
	(0.00170)	(0.00129)	(0.000269)	(0.000294)	(4.48e-06)
Observations	533,258	533,258	533,258	454,660	454,660
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Number of firms	78,598	78,598	78,598	78,598	78,598

Robust standard errors in parentheses.
*** denotes significance at the 1% level; ** at 5% level; * at 10% level.
Firm and year fixed effects included in all estimated specifications.
γ = scale effect = $(\beta_l + \beta_k + \beta_m - 1)$