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Antonin Bergeaud

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**PARIS SCHOOL OF ECONOMICS-EHESS
DOCTORAL DISSERTATION**



in Analyse et Politiques Économiques

Firm dynamics, innovation and productivity

By

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Firm dynamics, innovation and productivity

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ABSTRACT

This thesis studies different aspects of firm dynamics both theoretically and empirically. All chapters extensively rely to large microeconomic dataset that are used to test theoretical predictions. First chapter looks at the innovation premium, that is the response to workers' wage when their firm increases its R&D intensity and therefore becomes closer to the technological frontier. This response is evaluated using matched employers-employees data with information on the wage of 1% of all UK based workers. Second chapter focuses on the response to an export demand shock to a firm's innovation and productivity looking at all French firms with at least one patent and using both fiscal and customs micro data. Finally, the third chapter considers the role of factor adjustment costs, especially on corporate real-estate, on firms employment dynamism following a productivity shock. This chapter uses a large sample of single-establishment French firms.

Taken together, these three chapters explore different dimension of the response to firms to a demand and/or a productivity shock, either in terms of employment and wage, or in terms of innovation and size.

RÉSUMÉ

Cette thèse étudie différents aspects de la dynamique des firmes, à la fois de manière théorique et empirique. Tous les chapitres utilisent largement différentes bases de données microéconomiques pour tester les prédictions théoriques. Le premier chapitre s'intéresse au premium de l'innovation, c'est à dire la réaction du salaire des employés d'une entreprise qui augmente son intensité de R&D et qui devient ainsi plus proche de la frontière technologique. L'évaluation de cette réponse se fait en utilisant une base de donnée sur le salaire de 1% de des travailleurs basés au Royaume-Uni. Le second chapitre s'intéresse à la réponse de l'innovation et de la productivité des firmes à un choc de demande à l'export, considérant les entreprises françaises ayant au moins un brevet, et utilisant pour cela des bases de données à la fois d'origine fiscale ou provenant des douanes. Enfin le troisième chapitre étudie le rôle des coûts d'ajustement des facteurs de production, et en particulier de l'immobilier des entreprises, sur la dynamique de l'emploi des entreprises à la suite d'un choc de productivité. Ce chapitre utilise un large échantillon d'entreprise mono établissement française.

Pris tous les trois, ces chapitres étudient différentes dimensions de la réponse des firmes à un choc de demande ou de productivité, que ce soit une réponse en termes d'emploi, de salaire, d'innovation ou de taille.

Notice: chapter of this dissertation are based on self-containing research articles. Chapter 2 is based on a joint work with Philippe Aghion, Rachel Griffith and Richard Blundell, Chapter 3 is based on a joint work with Philippe Aghion, Marc Melitz and Matthieu Lequien and Chapter 4 is based on a joint work with Simon Ray. This explains that similar information can be given in multiple places of the thesis.

Table of Contents

1	Introduction	1
1.1	Summary of first chapter	1
1.2	Summary of second chapter	2
1.3	Summary of third chapter	4
2	The innovation premium to low skill jobs	7
2.1	Introduction	7
2.2	The Basic Evidence on Wages and Innovation	11
2.2.1	The data	12
2.2.2	More innovative firms pay higher wages	12
2.2.3	Our main empirical finding	18
2.3	A Simple Model	22
2.3.1	Production technology	23
2.3.2	Wage negotiation	23
2.3.3	Outsourcing	29
2.4	Further empirical evidence	31
2.4.1	Characteristics of occupations	31
2.4.2	Tenure of low-skilled workers	35
2.5	Summary and conclusion	36
3	The Impact of Exports on Innovation: Theory and Evidence	37
3.1	Introduction	37
3.2	Theory	41
3.2.1	Consumer optimization	41
3.2.2	Firm optimization	42

3.2.3	Innovation choice	42
3.2.4	Endogenous determination of λ	46
3.2.5	The direct and indirect effects of increased market size	48
3.2.6	The effect of an increased share of country D's consumption on French products	49
3.2.7	More general utility and R&D cost functions	51
3.3	Exporters and Innovators: data and descriptive statistics	53
3.3.1	Data sources	53
3.3.2	Sector breakdown and skewness	55
3.3.3	The innovation-export nexus	57
3.4	Empirical framework and results	62
3.4.1	Identification strategy: firm-level export shocks	62
3.4.2	Estimation	65
3.4.3	Baseline results	66
3.4.4	Additional results	68
3.4.5	Additional results	74
3.5	Conclusion	80
4	Adjustment Costs and Factor Demand: New Evidence From Firms' Real Estate	81
4.1	Introduction	81
4.2	Background	85
4.2.1	Data	86
4.2.2	Firms' mobility in France	86
4.2.3	Relocating behaviour and workforce growth	88
4.3	Model	90
4.3.1	Model setup	90
4.3.2	Solving the model	94
4.3.3	Results from simulations	97
4.4	Empirical evidence	104

4.4.1	Effect of a local relocation on employment dynamics	105
4.4.2	Effects of adjustment costs on employment dynamics	109
4.4.3	Implication in terms of misallocation	119
4.5	Conclusion	124
5	Conclusion	125
	Appendices	127
A	Appendix of Chapter 1	128
A.1	Data construction and additional description	128
A.1.1	Business Expenditures on Research and Development	128
A.1.2	Annual Survey on Hours and Earnings (ASHE)	130
A.1.3	Travel to work areas	134
A.1.4	Matching BERD and ASHE	137
A.1.5	Descriptive statistics	139
A.1.6	O*NET data	139
A.2	Decomposition of variance	143
A.3	Extending the model	144
A.4	Additional specifications	147
A.4.1	Different measures of income	147
A.4.2	Different functions of R&D	147
A.4.3	Other measures of innovation	150
A.4.4	Other robustness	150
B	Appendix of Chapter 2	157
B.1	Data description	157
B.1.1	Patent data	157
B.1.2	Firm-level accounting data	158
B.1.3	Trade data	160
B.1.4	Matching	160

B.1.5	Other data	162
B.2	Additional tables	162
C	Appendix of Chapter 3	171
C.1	Data description	171
C.1.1	Data sources	171
C.1.2	Variable construction and further descriptive statistics	173
C.2	Additional figures	179
C.3	Theory appendix	180
C.3.1	Model without friction	180
C.3.2	Existence of an interval of inaction	183
C.3.3	Results from simulation: the case of a positive aggregate productivity shock (+5%)	185
C.4	Additional empirical results	189
C.4.1	Robustness of results in section 4.4.1	189
C.4.2	Additional results	197
	Bibliography	202

List of Figures

2.1	Log hourly wage, by age	13
2.2	Share of workers in R&D firms at different wage	14
2.3	Log hourly wage and R&D intensity	15
2.4	Log hourly wage, by skill and age	19
2.5	Average log wage, by skill group	20
2.6	Tenure for workers by skill and quantile of R&D	35
3.1	Optimal innovation is higher for more efficient firms	44
3.2	Direct market size effect (increase in L)	45
3.3	Competition effect (increase in λ)	46
3.4	Determination of λ	48
3.5	Overall response of innovation to an increase in market size L	50
3.6	Lorenz curves - patents are more concentrated than exports, sales and employment	57
3.7	The share of innovators jumps at the top of the export distribution	61
3.8	Patenting increases more with demand for initially more efficient firms	67
3.9	Response to Demand by decile of productivity	73
4.1	Propensity to relocate and employment growth	89
4.2	Employment growth as a function of productivity shocks for different values of a	99
4.3	Share of relocating firms	100
4.4	Length of the non-relocating interval	101
4.5	Mean employment growth as a function of a	102
4.6	Covariance between real-estate volume and relocation cost	102
4.7	Aggregate output as a function of a	103
4.8	Inputs' price as a function of a	103
4.9	Relocation and employment dynamics - Quantile regression results	107

4.10	Propensity to relocate and employment growth: owners vs renters	111
4.11	Propensity to relocate and relocation costs as measured by the latent tax on capital gains	114
4.12	Relocation costs and employment dynamics.	122
4.13	Relocation frictions and misallocation	123
A.1	Outsourced R&D expenditures for 20 quantiles of total R&D intensity	129
A.2	Cumulative distribution function of log wage	138
A.3	Distribution of workers by skill and R&D of firm	140
C.1	Histogram of the distances between the place of departure and the place of settlement	176
C.2	Propensity to relocate against employment growth - Manufacturing and Services	179
C.3	Propensity to relocate against employment growth - Various regions	180
C.4	Employment growth as a function of productivity shocks for different values of a - 5% shock	185
C.5	Share of relocating firms - 5% shock	186
C.6	Length of the non-relocating interval - 5% shock	186
C.7	Mean employment growth as a function of a - 5% shock	187
C.8	Covariance between real-estate volume and relocation cost - 5% shock	187
C.9	Aggregate output as a function of a	188
C.10	Inputs' price as a function of a - 5% shock	188

List of Tables

2.1	Variance decomposition	11
2.2	Comparison of R&D and non R&D firms	16
2.3	Correlation between income and R&D intensity.	17
2.4	R&D intensity and hourly earnings at different skill levels.	21
2.5	Consequence of an error	33
2.6	Impact of decision	34
2.7	On the job and on-site training	34
3.1	Exports and innovation in the manufacturing sector	56
3.2	Exporters and innovators are bigger	59
3.3	Export and innovation premia	60
3.4	Baseline results	68
3.5	Other patent indicators	69
3.6	Control for firm size	70
3.7	Excluding leaders	71
3.8	Alternative definition of frontier	72
3.9	Control for productivity specific trend	74
3.10	Direct measure of competition	76
3.11	Other Dependent Variables - First Differences	78
3.12	Other Dependent Variables - Level	79
4.1	Key summary statistics - relocating locally and static firms	88
4.2	Value of parameters used in the simulation procedure.	98
4.3	Relocation and employment dynamics - Cross section results	106
4.4	Relocation and employment dynamics - Panel Fixed-Effect results	110
4.5	Relocation cost and relocation choice - Cross section OLS	115

4.6	Relocation cost and relocation choice - Panel Fixed-Effect results	117
4.7	Relocation costs and employment dynamics - Cross section results	120
4.8	Relocation costs and employment dynamics - Panel Fixed-Effect results	121
A.1	Distribution of employment and R&D	130
A.2	Skill classification	133
A.3	Demographics by skill level	135
A.4	Pay by skill categories	136
A.5	Construction of the sample	137
A.6	Matching results at the firm-year level	138
A.7	Variable description	139
A.8	Descriptive statistics of wage variables	140
A.9	Share of workers at each skill category and quantiles of R&D	141
A.10	Robustness to using different measures of income.	148
A.11	Testing different function of R&D	149
A.12	20 quantiles of R&D based on level of total R&D expenditures	151
A.13	Robustness to using different measures of R&D.	152
A.14	Robustness: Removing firms from the highest quantile of R&D expenditures.	154
A.15	Robustness: Removing firms with no R&D expenditures.	155
A.16	Robustness: Alternative measure of skill.	156
B.1	Exporters and innovators are bigger	163
B.2	Different trimming	163
B.3	Removing first years	164
B.4	Baseline results - Clustered standard errors	164
B.5	Control for firm size - Triadic applications	165
B.6	Control for productivity specific trend (2)	165
B.7	Alternative definition of frontier - Triadic patent applications	166
B.8	Other Dependent Variables - First Difference (2)	167
B.9	Other Dependent Variables - Level (2)	168

B.10 Other Dependent Variables - First Difference (2)	169
B.11 Other Dependent Variables - Level (2)	170
C.1 French <i>Départements</i> in 2013	174
C.2 Real estate prices and propensity to relocation across <i>départements</i>	175
C.3 Variables description	178
C.4 Frequency of relocations	189
C.5 Relocation and employment dynamics - All firms - Different distance thresholds - Cross section OLS	190
C.6 Relocation and employment dynamics - Growing firms - Different distance thresh- olds - Cross section OLS	191
C.7 Relocation and employment dynamics - Declining firms - Different distance thresholds - Cross section OLS	192
C.8 Relocation and employment dynamics - No entry - Cross section OLS	193
C.9 Relocation and employment dynamics - First Five Years - Cross section OLS	194
C.10 Statistics on changes in local characteristics following a relocation - Growing firms and declining firms	195
C.11 Relocation and employment dynamics - No entry - Cross section OLS	196
C.12 Summary statistics - Owners and Renters	197
C.13 Relocation cost and relocation choice - Remove tenure status transition - Cross section OLS	198
C.14 Relocation cost and relocation choice - Only local movers - Cross section OLS	199
C.15 Relocation cost and relocation choice - National level tax - Cross section OLS	200
C.16 Relocation cost and relocation choice - Cross section OLS - Within Labor Market Area relocations.	201

CHAPTER 1

Introduction

1.1 Summary of first chapter

In the first chapter,¹ we are interesting in looking at the wage premium to working in an innovative firm. It is a well-known result that firms that do more R&D tend to pay higher wage, if only because they have more rent to share with their workers. Using matched employee-employer data from the UK that we augment with information on R&D expenditures, we analyze the relationship between innovativeness and average wage income for a large sample of workers followed from 2004 to 2014.

We first show that more R&D intensive firms pay higher wages on average, and that this finding is robust to controlling for many observable characteristics of the worker and the firm, and to worker specific time-invariant unobservable features.

Our second and main finding is that the premium to working in more R&D intensive firms is higher for low-skilled workers than for high-skilled workers. This results may seem counter-intuitive at first sight, but it should not be understood as the fact that innovation mostly benefits the lowest skilled workers. On the contrary, as technology advances, demand for high skilled workers increases and they do better overall, but low skilled workers in innovative firms do better than other low-skilled workers.

To account for these findings, we develop a simple model of the firm where the main idea is that

¹This chapter is based on a joint work with Philippe Aghion, Richard Blundell and Rachel Griffith

in the most frontier and innovative firms, the potential damaging effect of a low skill workers is more important than in other firms. Concretely, this implies that the level of complementarity between low skill workers and other workers is the key driver of our empirical findings. The main assumption of the model are:

1. Innovative firms have organizational structure that show more complementarity between low and high skill workers.
2. Low skill workers in innovative firms have more firm-specific human capital than high skill workers.

The model predicts that indeed, if a firm is productive enough, the premium for working in an intensive firm is larger for low skill workers. Another prediction of the model is that R&D intensive firms tend to outsource their less crucial low skill occupations which is in line about the empirical findings that these firms have fewer low skill workers on aggregate.

We show empirical support for the main assumptions of the model, namely using the O*NET database which gives detailed information on the nature of different occupations. This clearly shows than indeed, low skill workers in R&D intensive firms work in occupations that require more training and emphasize the fact that the consequence of them making an error is more important than other workers. Another finding is that low skill workers stay longer in R&D intensive firms, which is not necessarily the case for high-skill workers, consistently with the view that they have more firm-specific human capital.

1.2 Summary of second chapter

In the second chapter,² we explore the causal link between export and innovation, by studying the response of a firm's patenting activities following an increasing export market. The

²This chapter is based on a joint work with Philippe Aghion, Matthieu Lequien and Marc Melitz

existing literature, either theoretical or empirical has clearly highlighted that firms involved in international trade are more productive, larger, more innovative and pay higher wage. This chapter aims at shedding a new light on the mechanism through which export and innovation are linked.

To do so, we build a simple model of trade and innovation with heterogeneous firms that predicts that a positive export shock should raise innovation and that this increase should be larger for more productive firms. This model namely highlights two coexisting channels:

1. following an increasing export market, the innovation effort increases for all firms because the accompanying rents increase with a firm's market size (*market size effect*), which is a well known theoretical results.
2. yet, innovation effort also decreases because competition toughens.

This *competition* effect dissipates with higher firm productivity. It is therefore most salient for the least productive firms and can potentially overturn the direct *market size* effect. To the best of our knowledge, this is the first time that these two effects are considered together in a heterogenous firm framework.

We then test this prediction with patent, customs and production data covering all French firms with at least one patent since 1994. To disentangle the direction of causality between innovation and export performance, we construct various firm-level export demand measures. These variables capture the extent to which demand fluctuations in a firm's foreign markets should influence its exports and through them weigh on its innovation decisions; but they remain exogenous to those firm-level decisions.

Our results confirm the predictions of the model. We namely show that patenting robustly increases more with demand for initially more productive firms. This effect is reversed for the least productive firms as the negative competition effect dominates. We then test more directly

the competition effect by considering export demand shocks from the most competitive countries (versus the least competitive countries).

1.3 Summary of third chapter

In the third chapter,³ we explore the effects of the costs associated with change in the volume of firms' premises on factors demand, notably on the firm-level dynamics of the workforce size. More generally, this research contributes to the question regarding the role of adjustment costs on the allocation of production factors by documenting the effect of a quantifiable cost that varies across time and across firms.

As a firm grows, it will eventually be constrained by the size of its premises. Conversely, if it declines, the firm will operate in suboptimal oversized premises. When access to adjacent lands or buildings is constrained, or if sublease of unused premises is not possible, adjustments of the premises are likely to be realized through local relocations of activities. Those local relocations are costly and the associated cost varies across firms notably because of the tax on realized real estate capital gains. For real estate owners, these relocations indeed require the sale of previously occupied premises and the payment of the tax. It entails firm-level variations in the adjustment costs that are empirically exploited in this study. As a result, we expect to see more frequent relocations for firms that are more dynamic in terms of employment; this is indeed confirmed in Figure below.

To guide the interpretation of our results, we build a general equilibrium model with heterogeneous firms from which we derive predictions on the effect of the level of the fixed costs associated with real estate adjustment on the workforce growth at different level of productivity shocks. In this framework, profit-maximizing firms are heterogeneous with respect to their

³This chapter is based on a joint work with Simon Ray

productivity level and make decisions on labor and real estate inputs in a context of adjustable real estate inputs conditional on paying a fixed cost. The level of these adjustment costs deter some firms from optimally adjusting their real estate inputs to the new productivity level and the complementarity between real estate and labor in the production process implies that it also affects firms' labor demand. We derive the existence of an interval of inaction for the difference in size between the optimal premises and the occupied ones in which firms do not adjust their real estate.

Other consequences of the model comes from the complementarity between real estate and labor which leads these firms to restrain employment growth as compared to their optimal employment growth they would observe had those firms adjusted their real estate. We show that the interval of inaction widens with the level of the adjustment costs and so do the number of firms affected. We also show that the non-relocating interval is not centered in zero and that a rise in the fixed adjustment costs has asymmetrical effects on the bounds of the interval. The effect of such a rise is larger in absolute value on the positive bound of the interval than the effect on the negative bound which implies that an increase in the fixed adjustment cost has an overall negative impact on mean firm-level employment growth. This asymmetry property strengthens with the level of the adjustment cost.

We test these predictions using microdata on French single-establishment firms from 1994 to 2013. We measure the level of the fixed costs associated with relocation by using the tax on capital gains. Different regression models confirm the theoretical predictions, namely that:

1. Relocation is associated with an increase (respectively decrease) in employment growth for firms that are growing (respectively declining).
2. The larger the (latent) fixed costs, the less likely a firm is to relocate.
3. The larger the (latent) fixed costs, the less dynamics the employment.

4. Overall, employment is negatively affected by the size of the tax on capital gain.

Our baseline results suggest that a reduction of the relocation costs, through a decrease of the share of the real-estate market value that would be paid as a tax on capital gains of 1 standard deviation, would increase the propensity to relocate of affected firms by 10% and would raise the yearly employment growth rate of the growing firms by 5%. Besides, by reducing job reallocation from the least productive firms to the more productive ones, such fixed adjustment costs generate misallocation and affect global output.

CHAPTER 2

The innovation premium to low skill jobs

2.1 Introduction

High and persistent income inequality in developed countries has attracted considerable attention, including most notably in the US and the UK (e.g. see [Deaton, 2013](#), [Atkinson, 1997](#) and [Piketty, 2014](#)); according to the OECD, workers in the top 10% of the wage distribution in the UK earn on average over 10 times more than workers in the bottom of the wage distribution; in the US it is almost 19 more. A leading explanation for the acceleration in income inequality over the past two decades, is that there has been an acceleration in the rate of skill-biased technical change (e.g. see [Krusell et al., 2000](#); [Acemoglu, 2002](#)).

In this chapter, however, we shall argue that while the prediction of a premium to skills holds at the macroeconomic level, it misses important aspects of the internal organization of innovating firms. More specifically, we use matched employer-employee data from the UK, which we augment with information on R&D expenditures, to analyze the relationship between innovativeness and average wage income at different skill levels across firms. Our main finding is that lower-skilled workers benefit more from working in more R&D intensive firms, relative to working in a firm which does no R&D) than higher-skilled workers. This finding is summarized by [Figures 2.5](#). In that Figure, we first see that higher-skilled workers earn more than lower-skilled workers in any firm no matter how R&D intensive that firm is (the high-skill wage curve always lies strictly above the middle-skill curve which itself always lies above the lower-skill curve).

But more interestingly the lower-skill curve is steeper than the middle-skill and higher-skill curve. But the slope of each of these curves precisely reflects the premium for workers with the corresponding skill level to working in a more innovative firm.

To rationalize the above finding, we propose a model in which more innovative firms display a higher degree of complementarity between low-skill workers and the other production factors (capital and high-skill labor) within the firm. Another feature of the model is that high-occupation employees' skills are less firm-specific than low-skill workers: namely, if the firm was to replace a high-skill worker by another high-skill worker, the downside risk would be limited by the fact that higher-skill employees are typically more educated employees, whose market value is largely determined by their education and accumulated reputation, whereas low-occupation employees' quality is more firm-specific. This model is meant to capture the idea that low-occupation workers can have a potentially more damaging effect on the firm's value if the firm is more innovative.

In particular an important difference with the common wisdom, is that here innovativeness impacts on the organizational form of the firm and in particular on complementarity or substitutability between workers with different skill levels within the firm, whereas the common wisdom view takes this complementarity or substitutability as given. Think of a low-occupation employee (for example an assistant) who shows outstanding ability, initiative and trustworthiness. That employee performs a set of tasks for which it might be difficult or too costly to hire a high-skill worker; furthermore, and perhaps more importantly, the low-occupation employee is expected to stay longer in the firm than higher-skill employees, which in turn encourages the firm to invest more in trust-building and firm-specific human capital and knowledge. Overall, such low-occupation employees can make a big difference to the firm's performance.

The model delivers additional predictions. In particular it also predicts that job turnover should be lower (tenure should be higher) amongst low-skilled workers who work for R&D-intensive

firms than for low-skilled workers who work for non-R&D intensive firms, whereas the turnover difference should be less between high-skilled workers employed by these two types of firms. This additional prediction is confronted to the data in the last part of the chapter.

The chapter relates to several strands of literature. First, there is the labor and wage literature, starting with the seminal work of [Abowd et al. \(1999\)](#); this literature has agreed that firms' heterogeneity play a large role in explaining wage differences across workers; however, there is no consensus in explaining which features of the firm account for such variation.¹ Other studies report a link between productivity and wage policy ([Cahuc et al., 2006](#) and [Barth et al., 2016](#) among others). [Song et al., 2015](#) cite outsourcing as a potential explanation for the raise of between firm inequality. We argue that a source of variation in firm's propensity to pay higher wages than other has to do with innovation intensity. This result echoes those of [Van Reenen \(1996\)](#), who showed that innovative firms pay higher wages on average, using information on public listed UK firms.

Second, there is the literature on wage inequality and skill-biased technical change (e.g. see [Acemoglu, 2002](#); [Goldin and Katz, 2010](#), [Acemoglu and Autor, 2011](#)). While this literature focuses on explaining the accelerated increase in the skill premium, we focus on the relationship between innovation and between-firm wage inequality, with the surprising finding that the premium to working in a more innovative firm is higher for lower skilled workers.

Third, there is the recent empirical literature on innovation, inequality and social mobility (e.g. see [Bell et al., 2016](#), [Aghion et al., 2015](#) and [Akcigit et al., 2017](#)). We contribute to this literature by introducing firms into the analysis and focusing on the relationship between innovation and between-firm income inequality.

Fourth, and more closely related to this chapter is the literature linking the aggregate dispersions in wages to productivity dispersion across firms ([Barth et al., 2016](#), [Timothy et al., 2004](#)).

¹For example, [Card et al. \(2016\)](#) assume that firm heterogeneity arises through TFP, but do not model what drives these differences in TFP

Part of this literature uses matched worker-employee data (see [Card et al., 2016](#) for a review) to investigate whether this correlation represents differences in workers selected into different firms, or the same type of worker being paid a different wage depending on the firm they work in. [Abowd et al. \(1999\)](#) pioneered the use of the two-way fixed effect model (firm and worker fixed effects) to study the effect on wages when a worker moves between firms. In a related literature that tries to measure rent-sharing elasticities, [Card et al. \(2016\)](#) report that, “*most studies that control for worker heterogeneity find wage-productivity elasticities in the range 0.05-0.15.*” And most closely related to our analysis is [Song et al. \(2015\)](#) which finds that “*between firm inequality accounts for the majority of the total increase in income inequality*” between 1981 and 2013 in the US. We contribute to this literature by bringing innovation into the picture, and by analyzing the relationship between innovation, wage income and occupation across firms.

Finally, we draw on the literature on wage inequality and the organization of the firm (e.g. see [Kremer, 1993](#), [Garicano and Rossi-Hansberg, 2006](#) and [Garicano, 2000](#)). We contribute to this literature by linking wage inequality, the organization of the firm, and its degree of innovativeness.

The remaining part of the chapter is organized as follows. In Section [2.2](#) we present our data and empirical methodology, and we establish our main empirical findings, namely that more innovative firms pay higher wages and that the premium to working in more innovative firms is higher for low skilled workers. In Section [2.3](#) we develop a simple model to account for these findings and list a few additional predictions from this model. In Section [2.4](#) we test those predictions. Section [2.5](#) collects our concluding remarks.

Table 2.1: Variance decomposition

	Variance		
	Overall	Within-firm	Between-firm
All	0.319	0.156	0.162
Low skill (1+2)	0.136	0.064	0.071
Intermediate skill (3+4)	0.209	0.112	0.097
High skill (5+6)	0.274	0.170	0.103

Notes: This table shows the between-firm and within-firm variance of the logarithm of hourly wage, calculated for each year from 2004 to 2014 and averaged over years. The decomposition of the overall variance is described in Appendix A.2. The data are matched employee-employer data from the UK; the sample is described in Appendix A.1, and includes 572,791 Workers in private corporation with at least 400 employees. Construction of skill levels is explained in Appendix A.1.2.3.

2.2 The Basic Evidence on Wages and Innovation

In this section we present our main empirical evidence on how average wage and average wage per type of occupation in the firm, depend upon the firms' innovativeness measured by R&D intensity. We start from the following very basic fact: Table 2.1 shows what is a well documented fact in many countries: in the UK over the last decade (2004-2014) the variance in wages *between* firms is at least as important in explaining wage inequality as the variance *within* firms.

Note that the literature has been relatively silent so far on why some firms pay higher wages than others for workers that appear similar. In a competitive labor market we would expect wages for similar workers to be the same across firms; heterogeneity in firm level technology might influence who is hired, but not the wages of any specific worker, since wages are taken as given by the firm. However, wages might deviate from marginal cost in imperfectly competitive markets. From the endogenous growth literature (e.g. see [Romer, 1990](#) and [Aghion and Howitt, 1992](#)), where innovation-led growth is motivated by the prospect of rents, it seems that innovation would be a prime candidate, and recent papers show the effect of innovation

on income inequality (e.g. [Aghion et al., 2015](#) and [Akcigit et al., 2017](#)).

2.2.1 The data

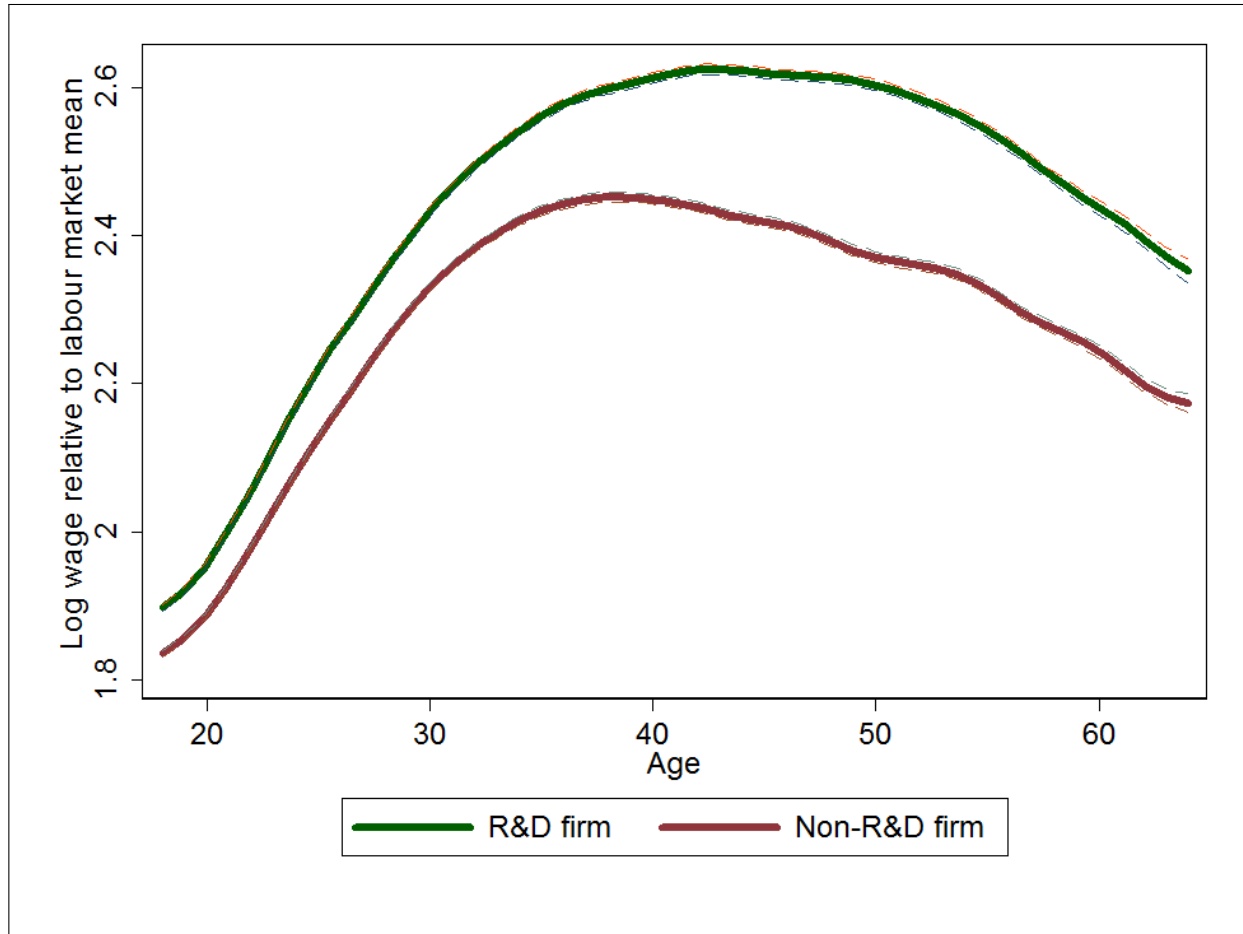
Hence our focus on the relationship between wages and innovativeness across firms. We document the correlation between R&D expenditure and wages using novel matched employer-employee data that also contains information on R&D expenditure for the period 2004 to 2014. The employee data come from Annual Survey of Hours and Earnings (ASHE), which is a random sample of 1% of the UK working population, matched to the Business Expenditure on Research and Development (BERD) survey. The data are longitudinal, we follow the same workers over time, and is recorded at the establishment level, with information on related establishments in the same firm. We focus on private companies (excluding the public sector, charities, etc) with more than 400 employees. We have information on around 50,000 employees who work in around 6,300 firms, giving us a total of around 580,000 observations. Further details on the data are given in [Appendix A.1](#).

2.2.2 More innovative firms pay higher wages

There are significant differences in the wages paid to workers in innovative firms compared to those working in non-innovative firms at all age, even after controlling for differences over time and within geographically separate labor markets (identified by travel to work areas). [Figure 2.1](#) shows the mean wage of workers in all occupations split by whether the firm that they work for does any R&D or not.

We also see this if we look at the share of workers that work in a firm that does any R&D across the wage distribution. In [Figure 2.2](#) we see that the share of workers that work in a firm that does any R&D increases from just over 20% for workers at the bottom of the wage distribution,

Fig. 2.1: Log hourly wage, by age



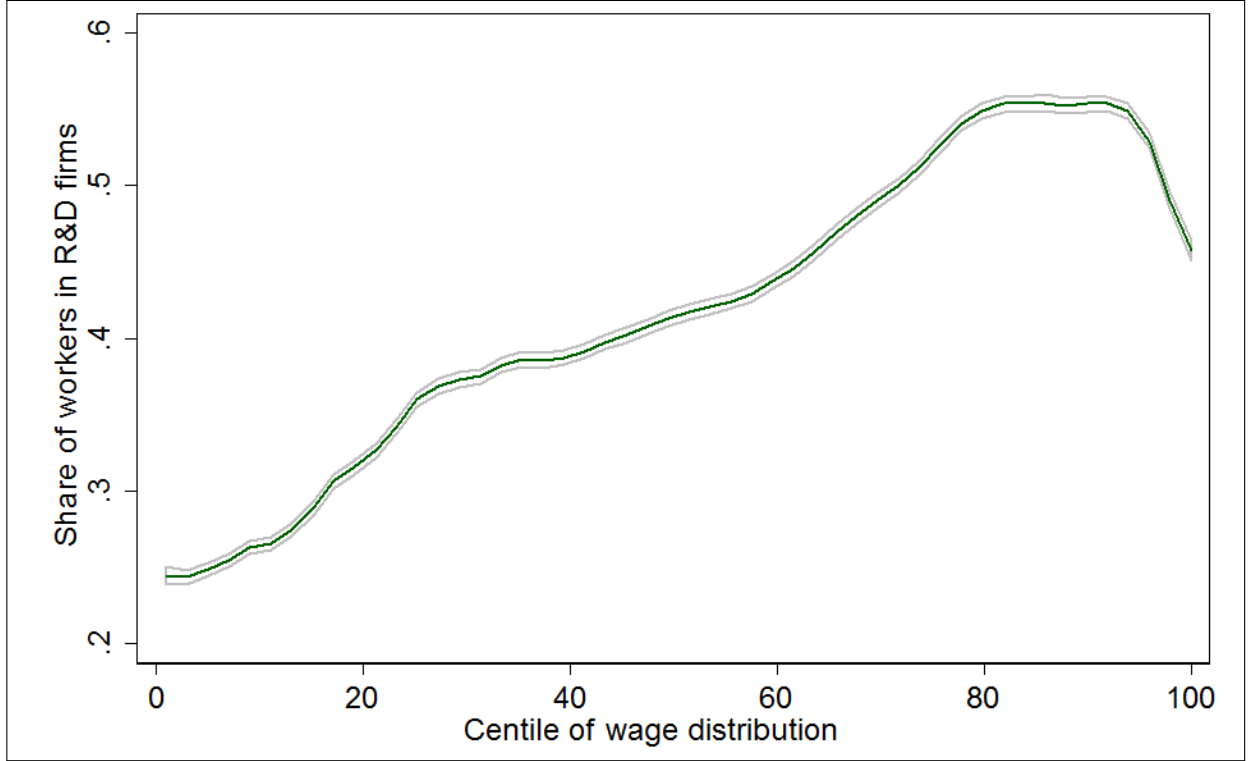
Notes: This figure plots age dummies from a regression of log hourly wage, controlling for separate year effects for each travel to work area (there are around 240 travel to work areas). The lower curve is for workers in non-innovative firms, the upper curve for workers in innovative firms. Innovative firms are defined as firm that have declared at least one pound in R&D expenditures over the period. 95% confident intervals are included.

to over 55% after the 80th percentile of the distribution where it plateaus. The share falls right at the top, where workers in the (low innovative) financial sector are heavily represented. This effect holds within innovative firms. The average wage in a firm increases with the firm's R&D intensity,² as shown in Figure 2.3.

Of course, workers in R&D firms might have different characteristics to those working in non-R&D firms. Table 2.2 shows that they are indeed more likely to be male, work full-time and

²In all the following, we will refer to R&D intensity as the ratio of total R&D expenditures divided by employment (see Appendix A.1.1).

Fig. 2.2: Share of workers in R&D firms at different wage



Notes: This figure plots the share of workers from innovative firms (defined as firms reporting a positive amount of R&D expenditure since 2000) at each percentile of the overall hourly wage distribution. All observations from our Final Sample from 2004 to 2014 are considered independently.

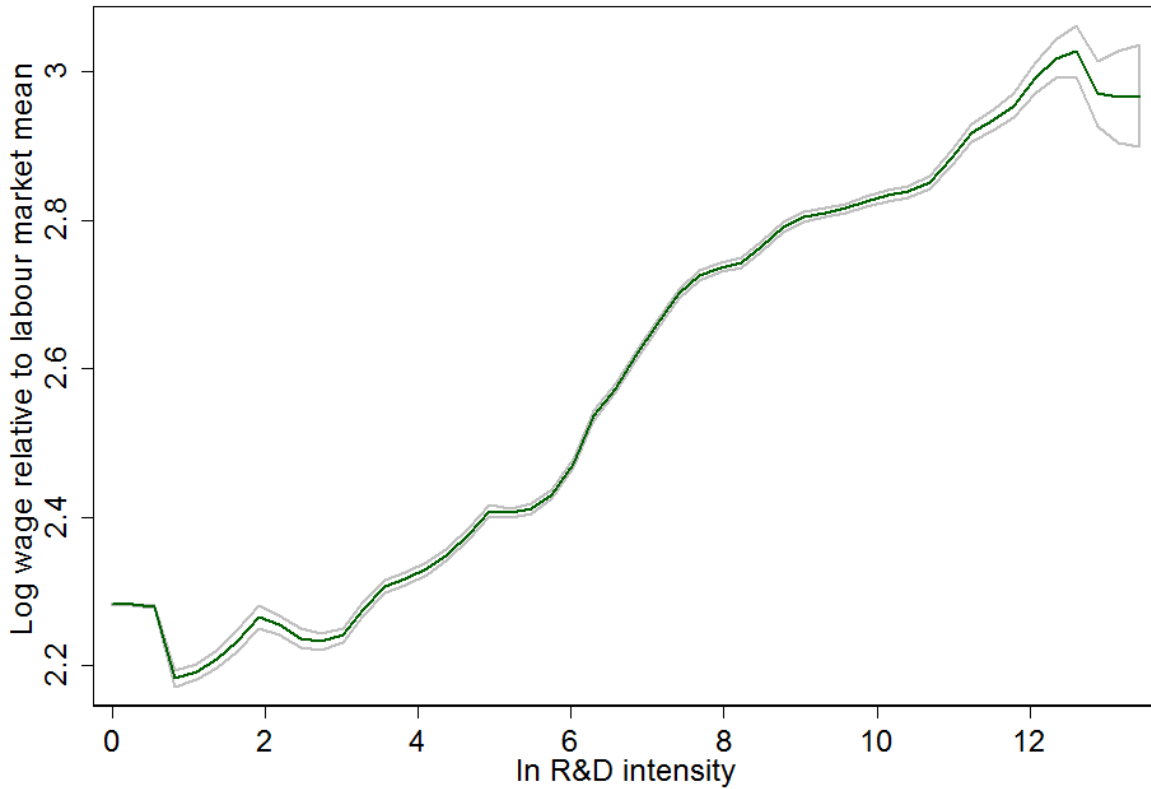
have longer tenure within the firm. R&D firms also differ from non-R&D firms in that they are larger (have a larger workforce).

To investigate whether these correlations hold up to controlling for other individual and firm characteristics we estimate the following equation:

$$\ln(w_{ijkft}) = \mathbf{X}'_{ift}\beta_1 + \mathbf{Z}'_{ft}\beta_2 + \beta_3\ln(1 + R_{ft}) + \epsilon_{ijkft}, \quad (2.1)$$

where i indexes individual, j occupation, k labor market, f firm and t years. The variable ϵ_{ijkft} includes fixed effects at differing levels depending on the specification (see details in the results tables) plus an idiosyncratic error. A labor market is defined as a travel to work area and there are around 240 such areas in the UK (see Appendix A.1.3). w_{ijkft} is mean hourly earnings, X_{ift}

Fig. 2.3: Log hourly wage and R&D intensity



Notes: This figure plots the logarithm of total hourly income against the logarithm of total R&D expenditures (intramural + extramural) per employee (R&D intensity). The x-variable is divided into 20 groups of equal size and one larger group of firms with no R&D (x-axis value set to 0). Groups of firms are computed yearly on the sample of private firms of more than 400 employees. See Tables A.5 and A.6 for more details.

are individual-firm level variables including age, gender, whether the job is full-time and tenure in the firm, Z_{ft} are firm characteristics including number of employees. R_{ft} is R&D intensity (R&D expenditure divided by number of employees). We use $\ln(1 + R_{ft})$ to accommodate values of 0 in firms that do not do any R&D; it is almost always equal to $\ln(R_{ft})$ given the magnitude of R&D expenditure, so we can interpret β_3 as the elasticity of wage with respect to R&D intensity. In Appendix A.4 we show robustness of our results to alternative functional forms and alternative measures of R&D. Tables A.1 and A.8 in the Appendix gives descriptive statistics of the key variables.

We estimate equation (2.1) using a fixed effect estimator. Card et al. (2014) suggest that,

Table 2.2: Comparison of R&D and non R&D firms

	Innovative firm		Current R&D firms	
	Yes	No	Yes	No
Employment	2,828	2,221	2,491	2,401
Hourly wage (£)	15.7	12.5	15.9	12.8
Share of male (%)	68	57	71	58
Share of full-time (%)	90	76	92	77
Share of high skilled workers (%)	30	18	31	19
Share of low skilled workers (%)	51	65	50	63
Age	40.5	38.1	41.1	38.3
Tenure	8.9	5.7	9.5	5.9
Firm-years	11,463	23,369	7,684	27,148
Observations	238,994	334,305	144,272	429,027

Notes: Employment is number of workers in the firm averaged over years, hourly wage is measured by total weekly earning divided by total paid hours (including overtime), high skilled workers include categories 5 and 6 (see Appendix A.1.2.3), low skilled include categories 1 and 2. Innovative firms are firms that report at least one pound of total R&D expenditure over the period, current R&D firms are those that report a positive amount of R&D expenditure in that period. A Student's test on the equality of each coefficient of column 1 (resp. 3) and column 2 (resp. 4) always reject the null hypothesis.

in a similar wage regression on a firm measure of rent, a bias in the estimated coefficient is expected because of small fluctuations in the firm level measurement of rent. They use an instrumental variables estimation. This problem mostly arises through short-term changes in sales and materials that influence the value added per employee which is their measure of rent. Our measure of rent is R&D expenditure which we argue is less likely to be affected by such accounting definitions. In addition, we show in Appendix A.4.3 that using the number of workers directly involved in R&D activities (a measure even less likely to be influenced by accounting definitions) does not affect our findings.

The estimated coefficients are shown in Table 2.3. In column (1) we use year-labor market fixed effects, in column (2) year-labor market-occupation fixed effect, in column (3) individual fixed effect and year effects and in column (4) firm fixed effect and year effects. The coefficient on

the R&D variable is always positive and significant; it decreases when firm or individual fixed effects are included.

What we see is that the correlations found in Figures 2.3 are robust to including a number of control variables that are likely to influence variation in income (age, experience, gender...). The positive correlation of R&D and income is also robust to including various combination of fixed-effect and its magnitude decreases a lot when moving from column (1) to (4). Note that including additive firm and individual fixed effects do not alter this finding.

Table 2.3: Correlation between income and R&D intensity.

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
ln R&D int	0.030*** (0.000)	0.016*** (0.000)	0.006*** (0.000)	0.001*** (0.000)
<i>Age</i>	0.057*** (0.000)	0.034*** (0.000)	0.085*** (0.000)	0.043*** (0.000)
<i>Age</i> ²	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Tenure</i>	0.022*** (0.000)	0.015*** (0.000)	0.008*** (0.000)	0.015*** (0.000)
<i>Tenure</i> ²	-0.00028*** (0.00001)	-0.00022*** (0.00001)	-0.00009*** (0.00001)	-0.00019*** (0.00001)
Firm Size	-0.033*** (0.000)	-0.010*** (0.000)	-0.007*** (0.000)	-0.023*** (0.002)
Full-Time	0.304*** (0.001)	0.120*** (0.001)	-0.001 (0.001)	0.186*** (0.001)
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
<i>R</i> ²	0.306	0.062	0.025	0.145

Notes: 572,786 observations. The dependent variable, log of wage, is measured by the gross hourly earning. Variables definitions are given in Table A.7. Column 1 includes year-labor market fixed effects, column 2 includes year-labor market-occupation fixed effects, column 3 includes year and individual fixed effects and column 4 includes year firm fixed effects. Heteroskedasticity robust standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

2.2.3 Our main empirical finding

The literature on skill-biased technical change (see for example [Goldin and Katz, 2010](#)) suggests that innovation drives inequality by driving up wages at the top end of the distribution. We add to this literature by looking at how the returns to working in a better (higher paying) firm vary between workers with different skill levels. We use a definition of skill based on a match between qualifications and occupations, defined in [Appendix A.1.2.3](#). We consider three skill groups. Low skilled occupations include manufacturing basic occupations, housekeeping, telephone sales. Medium skilled occupations include trades, specialist clerical, associate professionals. High skilled occupations include engineers and managers. [Figure 2.4](#) shows that throughout their life cycle, workers in high skill occupations receive significantly higher wage than other workers.

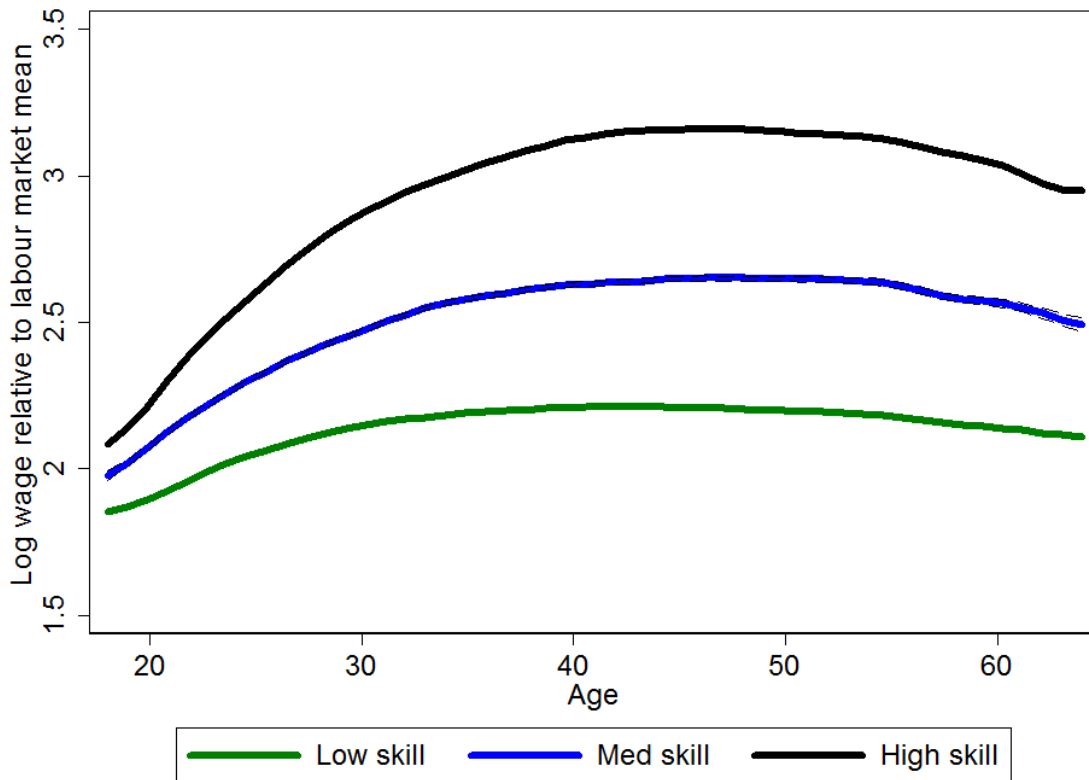
Surprisingly, going back to [Table 2.1](#), when we look by skill category we see that the within-skill group variance of wages across firms is relatively more important for low skill workers than high skill workers.

Our focus in this chapter is on the impact of innovativeness on between-firm wage inequality, in other words we want to look at how the returns to working in more innovative versus less innovative firms varies across the skill distribution.

[Figure 2.5](#) replicates [Figure 2.3](#) but splits workers by skill level. Workers in the highest skill categories (5+6) earn the highest wages, and these wages are on average similar across firms that do more or less (include zero) R&D. In contrast, workers in low skilled occupations earn substantially more if they work in a firm that has higher R&D intensity. The wage gradient with respect to R&D intensity is largest for low-skilled workers.

Highly innovative firms also hire fewer low-skilled workers. [Table A.9](#) in the Appendix shows that moving from the first vintile to the last one in terms of R&D intensity increases the share of high skilled workers (categories 5+6) from 13.7% to 63.8%.

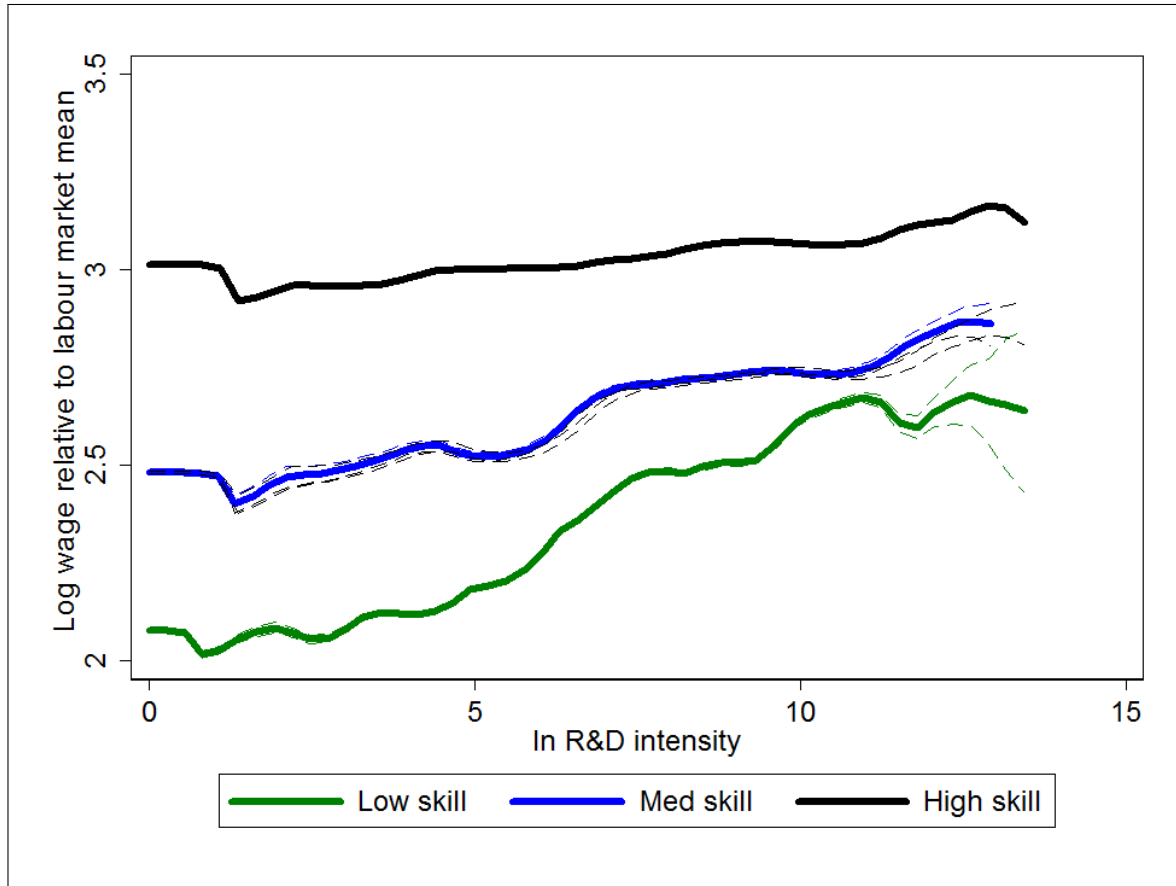
Fig. 2.4: Log hourly wage, by skill and age



Notes: This figure plots age dummies from a regression of log hourly wage, controlling for separate year effects for each travel to work area (there are around 240 travel to work areas). The lower curve is for workers in non-innovative firms, the upper curve for workers in innovative firms. Innovative firms are defined as firm that have declared at least one pound in R&D expenditures over the period. 95% confident intervals are included.

In order to see if this correlation is robust to controlling for differences between workers we estimate our preferred specification with individual fixed effects (column 3 of Table 2.3) separately for workers of different skill levels. In Table 2.4 column (1) we show results for low skilled workers (skill categories 1 and 2), in column (2) for intermediate skills (skill categories 3 and 4) and in column (3) for high skills (skill categories 5 and 6). The positive coefficient on R&D only holds for low and intermediate skill categories and is strongest for the former. In column 4 we pool all skill categories and allow the intercept and coefficient on R&D intensity to vary with the skill category. We see that compared to skill level 1, the interacted terms is

Fig. 2.5: Average log wage, by skill group



Notes: Vertical axis show the average of the logarithm of total hourly income of workers (standardized to have mean 0 across all skill categories when there is no R&D). Horizontal axis the quantile of R&D intensity of the firm, with 20 quantiles and an additional one indicating zero R&D as quantile 0. The bottom curve shows mean wage for low skilled workers, the middle line for intermediate skill and the top line for high skilled workers (see section A.1.2.3). 95% confident intervals are included.

always negative and is larger in absolute value as we move to higher skill levels.

One concern could be that high skilled workers receive a large part of their wage in the form of lump-sum bonuses at the end of the year and that these bonuses are not well captured by measures of weekly wages. This would particularly be an issue if high skilled workers receive larger bonuses in more R&D intensive firms. In Appendix A.4.1 we show that using yearly wages instead of weekly wages and including or excluding incentive payments does not affect our results.

The finding that the premium to working in a more innovative firm, is larger for lower skill

Table 2.4: R&D intensity and hourly earnings at different skill levels.

Skill category	Dependent variable: $\ln(w_{ijkft})$			
	(1) low (1+2)	(2) intermediate (3+4)	(3) high (5+6)	(4) All
ln R&D int	0.008*** (0.000)	0.002*** (0.001)	0.000 (0.000)	0.002*** (0.000)
*low skill				0.006*** (0.000)
*med skill				0.002*** (0.000)
Age^2	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Tenure	0.009*** (0.000)	0.006*** (0.001)	0.000 (0.000)	0.007*** (0.000)
$Tenure^2$	-0.00012*** (0.00001)	-0.00009*** (0.00001)	0.00003** (0.00001)	-0.00009*** (0.00001)
Firm Size	-0.005*** (0.000)	0.003* (0.002)	0.005*** (0.001)	-0.006*** (0.000)
Full-Time	-0.014*** (0.001)	-0.097*** (0.004)	-0.117*** (0.005)	-0.008*** (0.001)
skllow				-0.147*** (0.002)
sklmed				-0.065*** (0.002)
N	371815	95473	105482	572786
R^2	0.124	0.166	0.082	0.042

Notes: Definition of all variables is given in Table A.7. Individual and year fixed effects are included in all columns. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

workers, may look somewhat counter-intuitive and at odds with the literature on skill-biased technical change.³ In the next section we show how this finding can be rationalized. More specifically, we propose a model in which a firm’s innovativeness is reflected in the degree of complementarity between low skill and high skill workers.

2.3 A Simple Model

We develop a model where the complementarity between workers in “high-skilled” and “low-skilled” occupations within a firm increases with the firm’s degree of innovativeness. Another feature of the model is that the skills of workers in high-skilled occupations are less firm-specific (e.g. those are typically more educated employees, whose market value is largely determined by their education and accumulated reputation), whereas the skills of workers in low-skilled occupations are more firm-specific. Low-skill workers draw bargaining power from the fact that they can shed on their quality potential and underperform, which in turn reduces the firm’s output more when low-skill workers are more complementary to high-skill workers.

The model is meant to capture the idea that low-skilled workers can have a potentially more damaging effect on the firm’s value if the firm is more technologically advanced. This idea is in line with [Garicano and Rossi-Hansberg \(2006\)](#) where low-skilled employees draw problems and select between the easy questions which they solve themselves and the more difficult questions which they pass on to upper layers of the hierarchy. Presumably, the more innovative the firm, the harder difficult questions are to solve, therefore the more valuable high-skilled employees’ time is, and therefore the more important it is to have high-ability low-skilled employees so as to make sure that the high-skilled employees within the firm concentrate on the most difficult tasks. Another interpretation of the higher complementarity between low-skilled and high-skilled employees in more innovative firms, is that the potential loss from unreliable low-skilled

³ Similar findings have been derived by [Matano and Naticchioni \(2017\)](#) using Italian data.

employees is bigger in such firms: hence the need to select out those low-skilled employees which are not trustworthy.

2.3.1 Production technology

Suppose that the firm must employ one high-skilled and one low-skilled worker,⁴ with the following partial O-Ring production function (Kremer, 1993), where the high skilled worker has quality level (quality potential) Q and the low skilled worker has quality level (quality potential) q :

$$F(Q, q, \lambda) = \theta [\lambda Qq + (1 - \lambda)(Q + q)],$$

where $\lambda \in (0, 1)$ reflects the extent to which the firm is “innovative” (or “O-Ring” in Kremer, 1993’s terminology). We know from Caroli and Van Reenen (2001) and Bloom et al. (2014) that more innovating firms tend to have flatter internal organization, with more strategic complementarity between firm’s employees. In this version of the model, the value of λ is assumed to be exogenous and known by the firm. The timing of moves is as follows. First, the firm decides about the qualities potential (q, Q) of the two workers it hires. Then the firm hires the workers and negotiate separately with each of them. We solve the model by backward induction, starting with the wage negotiation and then moving back to the choice of qualities.

2.3.2 Wage negotiation

The firm engages in separate wage negotiations with each of the two workers. This negotiation will lead to the equilibrium wages $w^L(Q, q, \lambda)$ for the low skilled worker and $w^H(Q, q, \lambda)$ for the high skill worker. In its negotiation with its two workers, the firm takes into account the

⁴In Appendix A.3 we extend the model to more high-skilled and low-skilled workers.

fact that if the negotiation with the low-skilled worker fails, then the firm must fall back on a substitute low-skilled worker with quality q_L ⁵; similarly, if its negotiation with the high skilled worker fails, the firm must look for a substitute high skilled worker of quality Q_L . We assume that:

$$Q > Q_L > q > q_L > 1.$$

We also assume that it is relatively easier for the firm to find a substitute for the high skilled worker than to find a substitute for the low-skilled worker. The rationale for this assumption is that the ability of a low-skilled worker is harder to detect ex-ante, e.g. because there is less information the firm acquires ex ante based on the employee's CV (education, reputation). On the other hand, a high-skilled employee can show that she graduated from a leading university (Russell group, Ivy League etc.) or acquired a reputation.⁶

We thus assume that:

$$Q - Q_L < q - q_L. \tag{2.2}$$

Substitute low-skilled and high-skilled workers are paid wages w_L and w_H respectively, which we assume to be exogenous. Similarly, the low-skilled and high skilled incumbent workers have outside option \bar{w}^X with $X = H, L$ which are also exogenous. We assume: $w_L < w_H$ and $\bar{w}^L < \bar{w}^H$.

2.3.2.1 Equilibrium low skill wage

The firm's net surplus from employing the current low-skilled worker, is equal to:

$$S^F = \theta [\lambda Q + (1 - \lambda)] (q - q_L) - w^L(Q, q, \lambda) + w_L,$$

⁵Or equivalently accept that the current worker underperform at quality level q_L .

⁶Equivalently, the current high-skill worker, if kept by the firm, will not underperform much for reputational reasons.

whereas the low-skilled worker's net surplus is equal to

$$S^{LS} = w^L(Q, q, \lambda) - \bar{w}^L.$$

Assuming that the fraction β^L of the firm's net surplus goes to the low-skilled worker, with $\beta^L < 1$, or more formally:

$$S^{LS} = \beta^L S^F,$$

we immediately the following expression for the equilibrium wage of the low-skilled worker:

$$w^L(Q, q, \lambda) = \frac{\theta\beta^L}{(1 + \beta^L)} (q - q_L) (\lambda(Q - 1) + 1) + \frac{w_L\beta^L + \bar{w}^L}{(1 + \beta^L)} \quad (2.3)$$

2.3.2.2 Equilibrium high skill wage

Replicating the same argument for the high-skilled worker, under the assumption that a fraction β^H of the firm's net surplus accrues to the high-skilled worker, with $1 > \beta^H \geq \beta^L$, we obtain the following expression for the equilibrium wage of the high-skilled worker:

$$w^H(Q, q, \lambda) = \frac{\theta\beta^H}{(1 + \beta^H)} (Q - Q_L) (\lambda(q - 1) + 1) + \frac{w_H\beta^H + \bar{w}^H}{(1 + \beta^H)} \quad (2.4)$$

Since $\beta_H > \beta_L$ and $\frac{w_H\beta^H + \bar{w}^H}{(1 + \beta^H)} > \frac{w_L\beta^L + \bar{w}^L}{(1 + \beta^L)}$ and since from (2.3.2) and (2.2) that $(q - q_L) > (Q - Q_L)$ and $(Q - 1) > (q - 1)$, then we clearly have $w^H(Q, q, \lambda) > w^L(Q, q, \lambda)$ for all $\lambda \in (0, 1)$ and (q, Q) satisfying (2.3.2) and (2.2).

2.3.2.3 How innovativeness affects equilibrium wages

Taking the derivative of equilibrium wages with respect to λ yields:

$$\begin{aligned}\frac{\partial w^H(Q, q, \lambda)}{\partial \lambda} &= \frac{\theta \beta^H}{1 + \beta^H} (Q - Q_L)(q - 1) \\ \frac{\partial w^L(Q, q, \lambda)}{\partial \lambda} &= \frac{\theta \beta^L}{1 + \beta^L} (q - q_L)(Q - 1)\end{aligned}\tag{2.5}$$

Our baseline case is one where there is no difference in bargaining powers between high-skilled and low-skilled workers: this will be the case for example if the net surplus from employing each worker, is equally split between that worker and the firm. Then we have: $\beta^L = \beta^H$, which, together with Assumptions (2.3.2) and (2.2), immediately implies that:

$$\frac{\partial w^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w^H(Q, q, \lambda)}{\partial \lambda}.$$

In other words the low-skilled equilibrium wage increases more with λ (and thus with innovativeness) than the equilibrium wage of the high skill worker.

More generally, when $\beta^H \geq \beta^L$, this above result will hold whenever the following condition (2.6) is satisfied:

$$\frac{\beta^H(1 + \beta^L)}{\beta^L(1 + \beta^H)} < \frac{(q - q_L)(Q - 1)}{(Q - Q_L)(q - 1)}\tag{2.6}$$

This condition is in turn automatically satisfied when Q is sufficiently large and/or when Q_L is sufficiently close to Q , i.e. when high-skilled workers are sufficiently easy to replace with a substitute high-skilled worker.

Optimal choice of q

Having determined the equilibrium wages $w^H(Q, q, \lambda)$ and $w^L(Q, q, \lambda)$ for given q , Q and λ , we now move back and look at the firm's choice of qualities (q, Q) . We assume that the firm can choose any value of q and Q at no cost. The firm choice will maximize the firm's ex ante profit:

$$F(Q, q, \lambda) - w^H(Q, q, \lambda) - w^L(Q, q, \lambda),$$

with respect to $q > 1$ and $Q > 1$.

Assuming that $q \in [q, \bar{q}]$ and $Q \in [Q, \bar{Q}]$, this optimization problem immediately yields the equilibrium quality choice:

$$\begin{aligned} q &= \bar{q}; \\ Q &= \bar{Q}. \end{aligned}$$

More generally, suppose that the firm have needs to train the low-skilled worker to bring her from q_L to q at a convex cost $C(q - q_L) = \frac{1}{2}(q - q_L)^2$, and that training occurs before the wage negotiation. For simplicity, we consider the case where the bargaining surplus is split equally between the firm and each worker ($\beta_H = \beta_L = 1$). Then the firm chooses (q, Q) so as to:

$$(q^*, Q^*) = \operatorname{argmax}_{q_L < q < \bar{q} \quad Q_L < Q < \bar{Q}} \left\{ F(Q, q, \lambda) - w^H(Q, q, \lambda) - w^L(Q, q, \lambda) - \frac{C}{2}(q - q_L)^2 \right\}$$

With respect to Q , the problem remains linear which again leads to the corner solution $Q^* = \bar{Q}$.

With respect to q , the problem is concave so that by first order condition we obtain:

$$q^* = q_L + \frac{\theta}{2C} [\lambda(Q_L - 1) + 1],$$

where we implicitly assume that this value is lower than \bar{q} .

Note that q^ is increasing with λ : that is, more training is invested in low-skilled workers in more innovative firms.*

Next, we compute the equilibrium wage of low-skilled workers, which up to a constant is equal to:

$$w^L(\lambda) \equiv w^L(Q^*, q^*, \lambda) = \frac{\theta^2}{4C} (\lambda(Q_L - 1) + 1) (\lambda(\bar{Q} - 1) + 1),$$

so that:

$$\frac{dw^L(\lambda)}{d\lambda} = \frac{\theta^2}{2C} \left[(\bar{Q} - 1) (Q_L - 1) \lambda + \frac{\bar{Q} + Q_L - 2}{2} \right],$$

On the other hand,

$$w^H(\lambda) \equiv w^H(Q^*, q^*, \lambda) = \frac{\theta}{2} (\bar{Q} - Q_L) \left[\lambda \left(q_L + \frac{\theta}{2C} (\lambda(Q_L - 1) + 1) - 1 \right) + 1 \right],$$

so that:

$$\frac{dw^H(\lambda)}{d\lambda} = \frac{\theta}{2} (\bar{Q} - Q_L) \left[(q_L - 1) + \frac{\theta\lambda}{C} (Q_L - 1) + \frac{\theta}{2C} \right],$$

Then the inequality

$$\frac{dw^L(\lambda)}{d\lambda} > \frac{dw^H(\lambda)}{d\lambda}$$

boils down to:

$$2(q^* - q_L)(Q_L - 1) > (\bar{Q} - Q_L)(q_L - 1),$$

which is true from (2.3.2) and (2.2).

2.3.2.4 The effect of product market competition

One can augment the above model by introducing product market competition. One channel whereby competition might interact with the main effect of innovativeness on premium to a low

skilled worker, is that a firm having to hire a low-skill worker with quality q_L may be driven out of the market with positive probability by a competing firm. This will obviously increase the bargaining power of a low-skill worker. And it do so to a larger extent than it increases the bargaining power of a high-skill worker when $Q - Q_L \ll q - q_L$.

Predictions

The main predictions of the model so far can be summarized as follows:

Prediction 1: Low-skilled workers that remain in a firm benefit more from an increase in *R&D* of the firm (equivalent to an increase of λ) than high-skilled workers in that firm.

But in addition, the model generates the following predictions:

Prediction 2: Low-skilled workers stay longer in more innovative firms (as more time and money is invested in them to getting them from q_L to q^*);

Prediction 3: The main effect is stronger the lower the quality of potential replacements to a low-skilled worker (i.e. the lower q_L);

Prediction 4: The main effect is stronger in more competitive sectors if the quality of potential replacements to a low skilled worker is sufficient low;

2.3.3 Outsourcing

The model also speaks to the relationship between innovativeness and outsourcing: namely, more innovative firms tend to outsource low skill tasks more than less innovative firms. To see how we can generate this additional prediction, consider the following extension of the above model. There are now two low skill workers with quality q_1 and q_2 . Each firms has two kinds of tasks, one that require complementarity between the low and high skill workers and one that

does not. Like previously, there is one high skill workers of skill Q . The production function is now:

$$F(q_1, q_2, Q, \lambda) = \theta [\lambda q_1 Q + (1 - \lambda)(q_2 + Q)].$$

As before, workers engage in separate wage negotiations. But this time, if negotiations failed the task is outsourced to a worker with skill level q_L .

We also add to the model by assuming that the firm has to train each low skill worker to get more quality from her. However, the firm faces an overload constraint in its overall training activities. We model this overload constraint by assuming the following quadratic training costs function:

$$C(q_1, q_2) = C((q_1 - q_L) + (q_2 - q_L))^2.$$

Following wage negotiation, we have:

$$w^{L1} = \frac{\lambda Q \theta}{2} (q_1 - q_L) + w_L \tag{2.7}$$

$$w^{L2} = \frac{(1-\lambda)\theta}{2} (q_2 - q_L) + w_L \tag{2.8}$$

$$w^H = \frac{\theta}{2} [\lambda q_1 + (1 - \lambda)] (Q - Q_L) + w_H \tag{2.9}$$

The firm's ex ante payoff function thus becomes:

$$\frac{\theta}{2} [\lambda q_1 Q_L + (1 - \lambda)(q_2 + Q_L)] - 2w_L - w_H + \frac{q_L \theta}{2} [\lambda Q + (1 - \lambda)] - C(q_1, q_2).$$

Maximizing this payoff function with respect to (q_1, q_2) yields a corner solution with $q_2 = q_L$ whenever:

$$\lambda Q_L > (1 - \lambda),$$

or:

$$\lambda > \frac{1}{Q_L + 1},$$

in which case q_1 is optimally chosen at

$$q_1 = q_L + \frac{\lambda Q_L}{4C}.$$

We interpret this as a firm's decision to outsource task 2 so as to focus on training the worker assigned to task 1.

Prediction 5: A highly innovative (high- λ) firm will prefer to outsource the task that involves less complementarity between low and high skill workers.

2.4 Further empirical evidence

In this section we confront specific predictions of our model to the data.

2.4.1 Characteristics of occupations

Our model links the fact that low skill workers employed in more frontier (or higher R&D) firms get a higher wage premium than high skill workers, to the idea that low skilled workers become indispensable to the firm's success - i.e. more complementary with the firm's assets and higher skilled workers.

Measuring complementarity at the individual level is not straightforward. To show support for this prediction, we match in the O*NET data. The O*NET data provides detailed information on the characteristics of occupations in the US, which we assume are still relevant for the UK (more detailed are given in Appendix [A.1.6](#)).

We summarize the responses to four questions which provide evidence to the effect that low skilled workers are more complementary to other workers in high R&D firms than in low R&D firms.

1. What are the consequences of your making an error (1 = no consequences; 2, 3, 4, 5 = very large consequences)
2. What is the impact of decisions you make (1 = no impact; 2, 3, 4, 5 = very large impact)
3. On-site or in-plant training (none, up to 6 months, between 6 months and a year, a year or more)
4. On-the-job training (none, up to 6 months, between 6 months and a year, a year or more)

Consequence of error

Workers are asked to estimate the consequences of their making an error. They provide a grade between 1 (no consequence) and 5 (very large consequence) as spelled out above. In Table 2.5, we provide, for each skill level, the average values of the response in our sample across firms with three levels of R&D compared to firms with no R&D. The consequences of a worker in a low-skilled occupation making an error are larger in a higher-R&D firm than in a lower-R&D firm.

Impact of decision

Similarly, workers are asked to evaluate the impact of the decision they make. They provide grades reflecting their estimated impact, as specified above. We report the average values of the response across firms with three levels of R&D compared to firms with no R&D. The results are shown in Table 2.6. In particular, we see that the impact of decisions of a worker in a

Table 2.5: Consequence of an error

Skill level	Tercile of R&D intensity			
	None (1)	Low (2)	Middle (3)	High (4)
Low	1.00	1.02	1.12	1.14
Intermediate	1.00	1.00	1.02	1.03
High	1.00	1.02	1.00	0.99

Notes: R&D firms are split in three groups of equal size based on the value of their R&D expenditure per employee. Data are taken from O*NET and report the average of the score for the question “What are the consequences of you making an error?” across our final sample standardized to be equal to one for non R&D firms at each skill level.

low-skilled occupation, is larger in a high-R&D firm than in a low-R&D firm. The difference is small, but yet it is statistically significant.

Training

The last two questions spelled out above consider the duration of training low-skill workers receive across firms with different levels of R&D. Table 2.7 shows that in the highest R&D intensive firms, from 14.3% to 16.2% of low skill workers report having received training for more than one year, whereas only 6.4% to 7.2% of low skill workers report having received training for more than one year in no-R&D firms.

All these results are in line with the assumptions of our model, namely that: (i) low-skill workers are dedicated to tasks that involve more complementarity with other tasks in more R&D intensive firms (in other words, we vindicate the link between λ and the firm’s innovativeness); (ii) low-skill workers in more R&D-intensive firms have a higher need to develop firm-specific skills than they do in less R&D intensive firms and therefore they are in higher need to be trained (this is captured by the difference $q - q_L$ which increases with λ in our model).

Table 2.6: Impact of decision

Skill level	Tercile of R&D intensity			
	None (1)	Low (2)	Middle (3)	High (4)
Low	1	1.00	1.00	1.01
Intermediate	1	0.99	0.98	0.98
High	1	1.00	0.98	0.97

Notes: R&D firms are split in three groups of equal size based on the value of their R&D expenditure per employee. Data are taken from O*NET and report the average of the score for the question “What is the impact of decisions that you make?” across our final sample standardized to be equal to one for non R&D firms at each skill level.

Table 2.7: On the job and on-site training

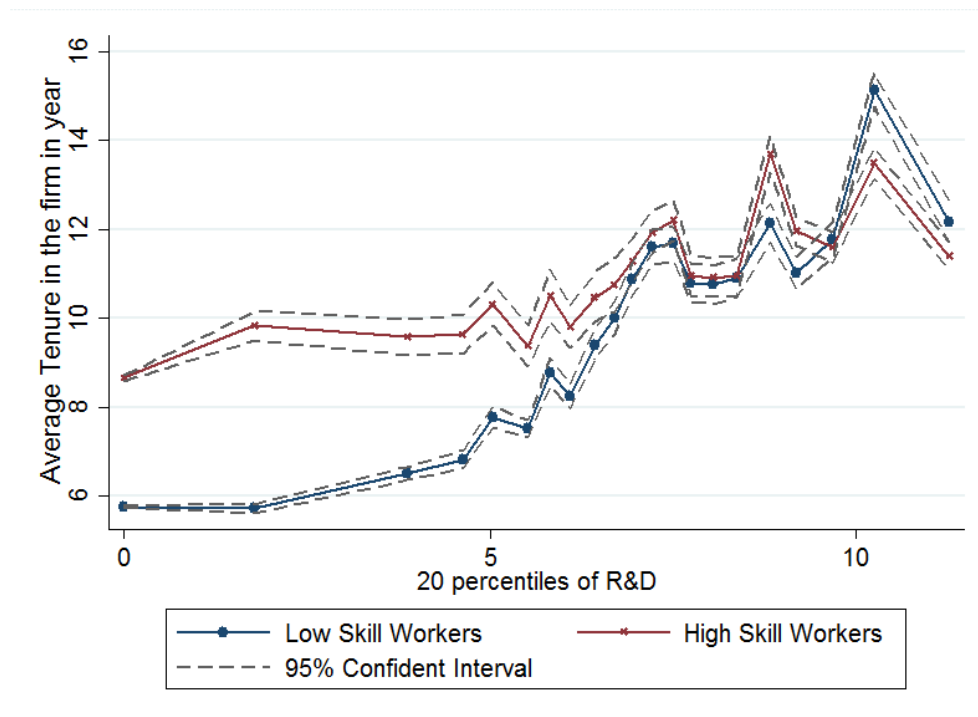
	Tercile of R&D intensity			
	None (1)	Low (2)	Middle (3)	High (4)
On-site or in-plant				
none	20.3	19.7	18.6	18.5
up to 6 months	65.6	64.3	59.6	54.4
6 months - 1 year	7.7	8.4	10.9	12.9
a year or more	6.4	7.6	10.9	14.3
On-the-job				
none	10.1	10.0	9.3	9.1
up to 6 months	74.8	72.5	66.1	59.9
6 months - 1 year	7.9	9.0	12.5	14.9
a year or more	7.2	8.5	12.1	16.2

Notes: R&D firms are split in three groups of equal size based on the value of their R&D expenditure per employee. Data are taken from O*NET and report the share of low-skill workers reporting having been trained for different durations.

2.4.2 Tenure of low-skilled workers

Our model predicts that lower skilled workers require more firm-specific training than higher-skilled workers, particularly in more innovative firms.⁷ Hence our Prediction 2 that low-skilled workers should stay longer in more innovative firms. On the other hand, there should be a smaller effect for innovativeness on high skilled workers turnover. This is indeed what we see from Figure 2.6.

Fig. 2.6: Tenure for workers by skill and quantile of R&D



Notes: Vertical axis show the average of the number of year spent in the firm. Horizontal axis the quantile of R&D intensity of the firm, with 20 quantiles and an additional one indicating zero R&D as quantile 0. The bottom curve shows mean tenure for low skilled workers and the top line for high skilled workers (see section A.1.2.3). 95% confident intervals are included.

⁷Note that in our model, low-skill workers in innovative firms will share some rents from firm-specific human capital investments in training. They draw bargaining power from the fact that they can shed on their quality potential and under perform, which in turn reduces the firm's output more when low-skill workers are more complementary to high-skill workers.

2.5 Summary and conclusion

In this chapter we used matched employee-employer data from the UK that we augment with information on R&D expenditures, to analyze the relationship between innovation and between-firm inequality. Our first finding is that more R&D intensive firms pay higher wages on average. Our second finding is that workers in low-skilled occupations benefit more from working in more R&D intensive firms than workers in high-skilled occupations. To account for these findings, we developed a simple model of the firm where the complementarity between employees in “high-skilled occupation” and “low-skilled occupation” within the firm increases with the firm’s degree of innovativeness. An additional prediction of the model, which we also confronted to the data, is that workers in low-skilled occupations stay longer in more innovative firms.

Our analysis can be extended in several directions. One would be to look at whether, as our model predicts, the (low-skilled) occupations that yield more return to innovativeness (i.e. for which wage increases more with innovativeness) are more “relational”. A second idea is to explore further whether more innovative firms provide more training to workers in low-skilled occupations. Third, our model predicts that our main effect (namely that workers in low-skilled occupations benefit more from working in a more innovative firm) is stronger in more competitive sectors or in areas where potential replacements for incumbent workers in low-skilled occupations are of lower quality: these predictions can be tested using our data. Fourth, we used R&D investment as our measure of innovativeness, and one could use other measures such as patenting. Finally, one may want to look at subgroups of agents within the high- and low-skilled occupation categories. In particular we should look at whether the premium to working in a more innovative firm, is not larger at the very top end of the occupation distribution. One first place to look at, are CEOs, taking into account their total revenues (wage income plus capital income). These and other extensions of the analysis in this chapter await further research.

CHAPTER 3

The Impact of Exports on Innovation: Theory and Evidence

3.1 Introduction

Does firms' access to export affect innovation? Modern trade and growth theories (Grossman and Helpman, 1991b; Acemoglu, 2009; Aghion and Howitt, 2009) suggest it should, if only because improved access to export markets should increase the *size of markets* that can be appropriated by successful innovators. Moreover, we know that trade induces knowledge spillovers. The *knowledge spillover* effect of trade underlies the work of Coe and Helpman (1995) among others.¹ However, on the empirical side, the question of how trade and more specifically *exports* should affect firms' innovation performance, has received little attention until recently (see our literature review below).

In this chapter we use exhaustive firm-level data covering all French exporting firms to analyze how new export opportunities affects exporting firms' innovation performance. One of the most striking features that emerges from this data is a massive correlation between export and innovation performance across firms. This holds both at the extensive margin (exporters are

¹Coe and Helpman (1995) construct, for each country, measures of domestic and foreign R&D capital stocks, where the latter are weighted averages of the domestic stocks of trade partners. They find that foreign R&D appears to have a beneficial effect on domestic productivity, and that the effect increases in strength with the degree of openness. Hence, not only are there important spillovers, but there is also some evidence that these are mediated by trade. However, one may argue that even if a correlation is observed between domestic productivity and foreign research, this may simply represent the outcome of common demand or input price shocks. Weighting the contribution of foreign research using data on bilateral trade flows, as in Coe and Helpman (1995), is likely to mitigate this problem but will not overcome it altogether.

substantially more likely to innovate, and innovators are more likely to export) as well as the intensive margin (large exporters tend to be big innovators and vice-versa). We describe these relationships in much more detail in Section 3.3. Does this correlation reflect a causal effect of export on innovation, or the effect of innovation on exports, or both? How does the innovation behavior of a firm react to its export markets' conditions? This chapter is a first attempt at understanding these firm-level patterns connecting innovation and trade using the matching between patenting, balance sheet, and customs exhaustive datasets.

In the first part of the chapter we develop a simple model of trade and innovation with heterogeneous firms. The model builds on Mayer et al. (2014) but adds the innovation dimension to it. It features a continuous set of firms indexed by their heterogeneous production costs. Innovation allows firms to reduce their production costs by an amount that increases with the size of the innovation investment. Think of French firms which export to China. An increase in Chinese demand for French firms' products, will have two main effects on firms' innovation incentives. First, a direct market size effect: namely, the expanded market for exports will increase the size of innovation rents and thereby increase French firms' incentives to invest more in innovation. Second, a competition effect: namely, the expanded market for exports may attract new firms into the Chinese market and more generally it will raise competition between exporters into that market. This competition effect dissipates with higher firm productivity. It is therefore most salient for French firms with initially higher production costs (these firms will suffer more than -or at the expense of- more efficient exporting firms). Hence the prediction that a positive export shock should raise innovation more in more frontier firms; and that it may induce less innovation for those firms that are far from the frontier.

In the second part of the chapter we take this prediction to the data. More specifically, we merge three exhaustive firm-level datasets - patenting data, production data, and customs data-, which cover the whole population of French firms to analyze how the access to export markets affects the stock and quality of patents by these firms.

The patent data are drawn from PATSTAT (Spring 2016 version) and contain information on all granted patents, including the country of residence of the applicant and a citation network between these patents. An algorithm matches a French firm’s name with its unique administrative identifier, which allows us to link the innovation activities of a firm with all other firm data sources. The production datasets FICUS and FARE, from INSEE/DGFiP, contain balance sheet information for each firm registered in France from 1993 to 2012 (total and export sales, number of employees, sector, etc.). French customs trade data (1993-2014) cover nearly comprehensive export flows by firm and destination at a very detailed level of product disaggregation (over 10,000 product categories). We complement these firm-level data sets with bilateral trade data from BACI ([Gaulier and Zignago, 2010](#), updated to cover the period 1995-2013) at the product level (at a slightly higher level of aggregation than our French firm-level export data); and with country-level data (primarily GDP).

To disentangle the direction of causality between innovation and export performance, we construct a firm-level export demand variable following [Mayer et al. \(2016\)](#). This variable responds to aggregate conditions in a firm’s export destinations but is exogenous to firm-level decisions (including the concurrent decisions for export-market participation and the forward looking innovation response). We show that: (i) Firms that are initially more productive (closer to their sector’s technology “frontier”) strongly respond to a positive export demand shock by patenting more; (ii) this effect dissipates for firms further from the “frontier” and is reversed for a subset of initially less productive firms. These results confirm the predictions of the model for both, a *market size* and a *competition effect* of the export shock.

Our analysis relates to several strands of literature. There is first the theoretical literature on trade, innovation and growth (e.g. see [Grossman and Helpman, 1991a,b²](#)). We contribute to this literature by uncovering a new -indirect- effect of market size on innovation working through competition, and by testing the market size effects of export expansion on innovation using

²See also [Akcigit et al. \(2014\)](#).

exhaustive firm-level data. Second, our chapter relates to recent papers on import competition, innovation and productivity growth (e.g. see [Bustos, 2011](#); [Bloom et al., 2016](#); [Iacovone et al., 2011](#); [Caldwell and Tabellini, 2015](#); [Autor et al., 2016](#)). These papers show that increased import competition induces firms to innovate more in order to escape competition as in [Aghion et al. \(2005\)](#).³ Instead we look at how the export side of trade affects innovation.

Most closely related to our analysis in this chapter are [Clerides et al. \(1998\)](#), [Bernard and Jensen \(1999\)](#) and [Lileeva and Trefler \(2010\)](#), which look at the effects of exports on productivity. In particular, [Lileeva and Trefler \(2010\)](#) provide evidence of a causal effect on export on productivity and innovation by using the US tariff cut imposed in 1989 by the new Free Trade Agreement (FTA) between US and Canada, as an instrument for export expansion. Their main conclusion is that the FTA induced productivity gains by Canadian firms that saw their access to the US market improved by the FTA. Moreover, focusing on a small subsample of 521 firms for which they have survey information on innovative investment, the authors show that firms in that sample which experience higher productivity growth also invested more in technology adoption and product innovation. We add to their analysis in three main respects: first, by uncovering an indirect- competition-enhancing effect of increased export markets; second, by showing that this effect leads to the market size effect of a positive export shock, being stronger for more frontier firms; third, by using patenting data to measure firms' innovation performance and by merging these data with exhaustive administrative and customs data covering the whole population of French firms.

The remaining part of the chapter is organized as follows. Section [3.2](#) develops our model of export and innovation, and generates the prediction that the market size effect of a positive export shock, is stronger for more frontier firms. Section [3.3](#) briefly presents the data and show some descriptive statistics on export and innovation. Section [3.4](#) describes our estimation

³Interestingly, in this chapter we use *firm-level* competition data, whereas [Aghion et al. \(2005\)](#) as well as previous papers by [Nickell \(1996\)](#) and [Blundell et al. \(1999\)](#) regress innovation and/or productivity growth on *sectoral* measures of product market competition.

methodology and present our empirical results and Section 3.5 concludes.

3.2 Theory

The model in this section is essentially a closed economy short-run version of the model in Mayer et al. (2014), augmented with innovation. We consider (all) French exporting firms that are selling in some export market destination D , and we let N denote the number of French firms that could potentially export. We let L denote the number of consumers L in that destination – with income normalized to 1, and we assume that these consumers spend a share η_F of their income on French goods. Suppose that the representative consumer in country D has utility for good i which is quadratic⁴ and equal to:

$$u(q_i) = \alpha q_i - \frac{\beta q_i^2}{2},$$

where $\alpha > 0$ and $\beta > 0$.

3.2.1 Consumer optimization

The representative consumer solves:

$$\max_{q_i \geq 0} \int_0^M u(q_i) di \quad \text{s.t.} \quad \int_0^M p_i q_i di = 1,$$

which yields by first order condition the inverse residual demand function (per consumer):

$$p(q_i) = \frac{u'(q_i)}{\lambda} = \frac{\alpha - \beta q_i}{\lambda}, \tag{3.1}$$

⁴As we argue below, the analysis can be extended to a broader class of utility functions, in particular to those that satisfy Marshall's Second Law of Demand, whereby firms' inverse residual demand becomes more inelastic as consumption q increases.

where $\lambda = \int_0^M u'(q_i)q_i di > 0$ is the corresponding Lagrange multiplier, also equal to the marginal utility of income.

3.2.2 Firm optimization

Consider a firm with marginal cost c facing demand conditions λ . This firm chooses the output per consumer $q(c, \lambda)$ to maximize operating profits $L [p(q)q - cq]$. The corresponding first order condition yields

$$q(c, \lambda) = \frac{\alpha - c\lambda}{2\beta}.$$

This in turn leads us to the following expressions for equilibrium revenues and profits:

$$r(c, \lambda) = \frac{\alpha^2 - (c\lambda)^2}{4\beta\lambda},$$

and

$$\pi(c, \lambda) = \frac{(\alpha - c\lambda)^2}{4\beta\lambda}.$$

In particular we see that $\pi(c, \lambda)$ is decreasing in c and λ . Below we shall interpret λ as a measure of the intensity of product market competition.

3.2.3 Innovation choice

A firm is characterized by its baseline cost \tilde{c} . The firm can reduce its actual marginal cost of production c below its baseline cost by investing in innovation. More formally, we assume that:

$$c = \tilde{c} - \varepsilon k,$$

where k is the firm's investment in innovation and $\varepsilon > 0$. Without loss of generality, we assume that the cost of innovation is quadratic in k , equal to $c_I k + \frac{1}{2} c_{I2} k^2$.⁵

Thus a firm with baseline cost \tilde{c} will choose its optimal R&D investment $k(\tilde{c}, \lambda)$ so as to maximize:

$$L\pi(\tilde{c} - \varepsilon k, \lambda) - c_I k - \frac{1}{2} c_{I2} k^2.$$

From the envelope theorem, the optimal R&D investment $k^*(\tilde{c}, \lambda)$ satisfies the first order condition:

$$\frac{\varepsilon L}{2\beta} (\alpha - (\tilde{c} - \varepsilon k^*) \lambda) = c_{I2} k^* + c_I, \quad (3.2)$$

with a corner solution with no innovation ($k^*(\tilde{c}, \lambda) = 0$) for high baseline cost firms, characterized by:

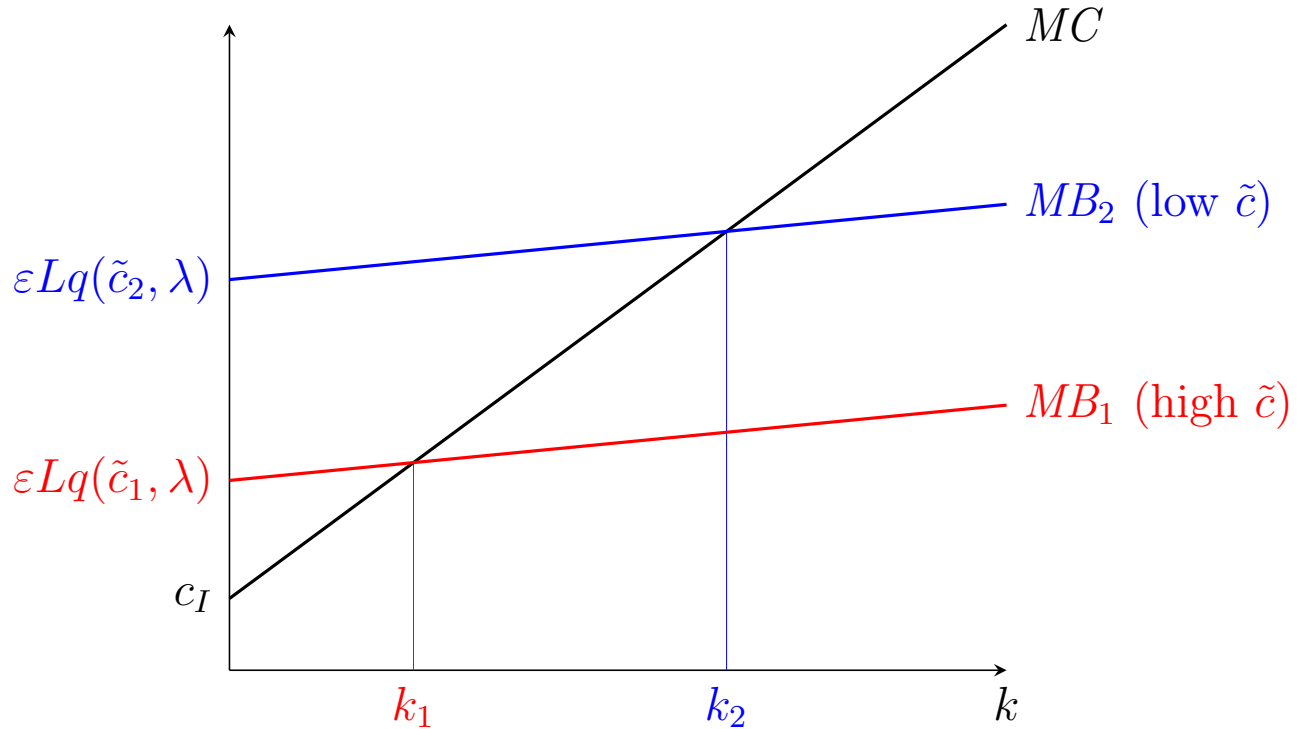
$$\tilde{c} > \frac{1}{\lambda} \left(\alpha - \frac{2\beta c_I}{\varepsilon L} \right).$$

Figure 3.1 describes the determination of the optimal innovation investment as the intersection between the marginal cost and marginal gain of innovation, respectively the right and left hand side of equation 3.2. As long as the marginal gain is above the marginal cost of investing in R&D, the firm wants to invest more, because the marginal profit made by investing one more unit of R&D, at R&D level k , exceeds its cost. The second order condition ensures that the slope of the marginal cost is strictly larger than the slope of the marginal gain, otherwise firms end up doing infinite R&D. When comparing a more productive firm (lower baseline cost, blue curve) and a less productive one (red curve), we see that they face the same marginal cost curve and have the same slope for the marginal gain, only the intercept of the marginal gain is different. Lower \tilde{c} firms have a higher intercept, thus a higher marginal gain for a given level of R&D, and therefore invest more in R&D. Firms with costs too high don't innovate: the

⁵Since we only consider a single sale destination D for our firms, we are implicitly assuming that the innovation is directed at the delivered cost to consumers in D . We should thus think of innovation as specific to the appeal/cost trade-off to consumers in D .

intercept of their marginal gain falls below c_I , so that even their first innovation unit would not be worth its cost.

Fig. 3.1: Optimal innovation is higher for more efficient firms



The impact of an increase in market size or competition on innovation

Marginal costs do not vary with L or λ , only the marginal gain curve is modified.

Figure 3.2 shows how innovation responds to an increase in market size. Both the intercept and the slope of the marginal gain curve increase. This leads to an unambiguous higher investment in innovation, for all firms; yet this innovation increase is stronger for more productive firms.

More generally, we have:

$$\frac{\partial^2 k}{\partial L \partial \tilde{c}} < 0.$$

An increase in the market size makes some firms begin R&D (those with the intercept of the marginal gain just below c_I).

Fig. 3.2: Direct market size effect (increase in L)

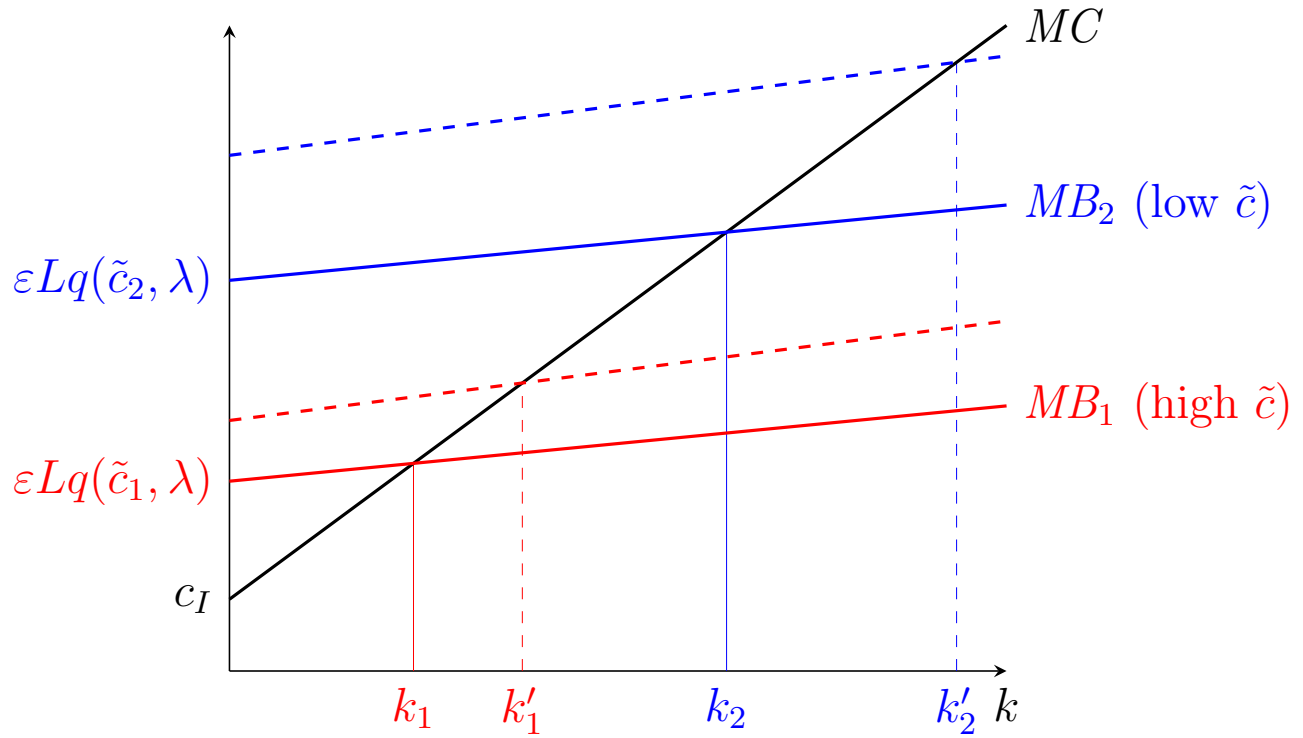
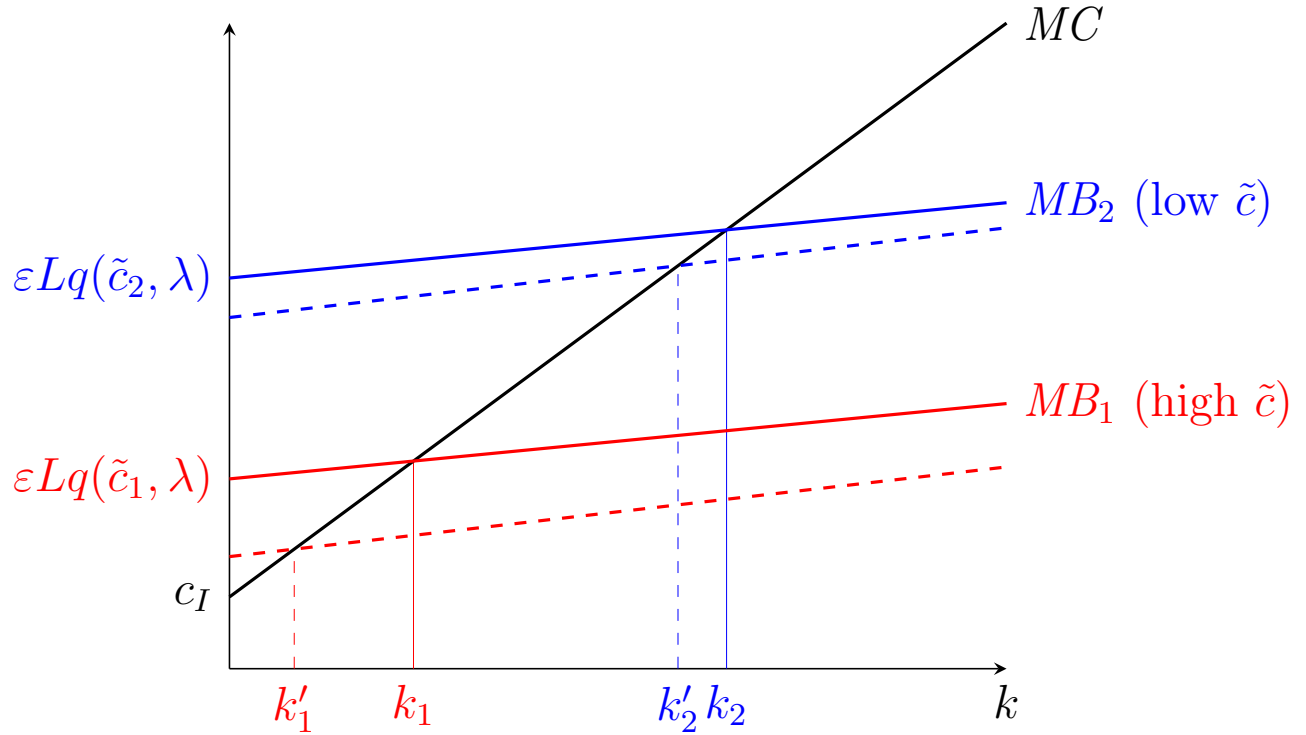


Figure 3.3 shows how innovation responds to an increase in λ . The marginal gain slope increases but its intercept decreases; however the new dotted curve remains below the old plain one at least until it meets the marginal cost curve. Therefore tougher competition reduces investment in innovation for all firms. Furthermore an increase in λ decreases more the intercept when \tilde{c} is bigger, so that a given competition increase reduces innovation more in less efficient firms:

$$\frac{\partial^2 k}{\partial \lambda \partial \tilde{c}} < 0.$$

Besides an increase in λ will make some firms stop R&D.

Fig. 3.3: Competition effect (increase in λ)



In the next subsection we endogenize the competition variable λ by linking it to aggregate market size L and the resulting equilibrium mass of competing firms under free entry.

3.2.4 Endogenous determination of λ

We shall focus attention on the free-entry equilibrium where the marginal firm is indifferent between paying a fixed ex post operating cost F and not entering the export market. Since operating profit is monotonic in a product's baseline cost \tilde{c} , the cutoff baseline cost \hat{c} of the marginal firm will satisfy:

$$L\pi(c(\hat{c}, \lambda), \lambda) = F, \tag{3.3}$$

where the LHS corresponds to the aggregate ex post profit the firm makes by entering the export market. Thus, only those French firms with baseline cost $\tilde{c} \leq \hat{c}$ will find it profitable to export to country D .

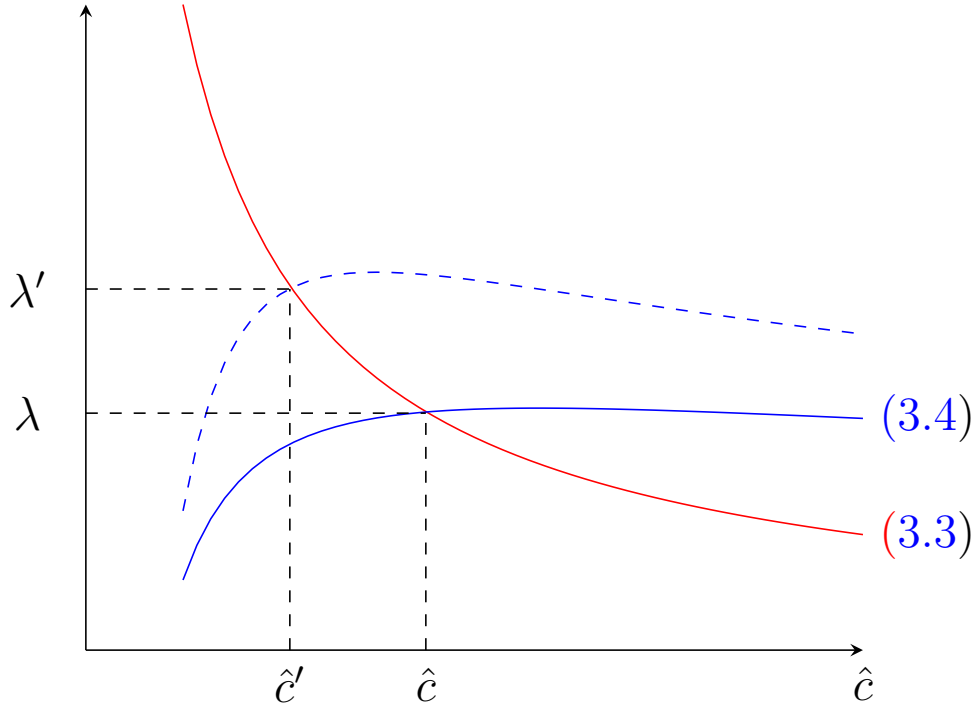
In fact the short-run equilibrium value of the baseline cost cutoff \hat{c} and the equilibrium value of the competition variable λ will be jointly determined by (3.3) and by an aggregate budget constraint. This budget constraint states that the aggregate spending by country D 's consumers on all exported products from the N exporting countries to D , must be equal to the aggregate revenue of country D 's consumers spent of French products, i.e. must equal η_F . More formally, letting $\Gamma(\tilde{c})$ denote the distribution of baseline costs across French firms, the budget constraint can be expressed as:

$$N \left[\int_0^{\hat{c}} r(c(\tilde{c}, \lambda), \lambda) d\Gamma(\tilde{c}) \right] = \eta_F. \quad (3.4)$$

Together, the above two equations (cutoff profit and budget constraint) jointly determine the toughness of competition λ in country D and the baseline cost cutoff \hat{c} as functions of market size L , the number of potential French exporters N , and the share η_F of country D 's consumption spent on French products.

In Figure 3.4 we represent the above two equations in the (\hat{c}, λ) space. The upward-sloping curve (2) represents equation (3.3) whereas the downward-sloping curve (1) represents equation (3.4). In particular consider the effect of an increase in N , which can be seen as a pure exogenous increase in competition. This will shift curve (2) upward, as for any given value of \hat{c} an increase in N must be offset by an increase in λ in order to keep the LHS of (3.4) constant equal to η_F . But then the equilibrium value of λ must increase whereas the equilibrium value of \hat{c} must decrease, as shown in Figure 3.4.

Fig. 3.4: Determination of λ



3.2.5 The direct and indirect effects of increased market size

The free-entry and budget balance conditions determine λ as an increasing function of L . Indeed, from equation (3.3), either \hat{c} or λ or both variables must increase in response to an increase in market size L . Now suppose for a moment that \hat{c} increases but λ decreases. Then the LHS of (3.4) should increase since: (i) the integration interval $[0, \hat{c}]$ expands; (ii) for any \tilde{c} in that support, $c(\tilde{c}, \lambda) = C$ must go down as $k(\tilde{c}, \lambda)$ would increase; therefore

$$r(c(\tilde{c}, \lambda), \lambda) = \frac{\alpha^2 - (C\lambda)^2}{4\beta\lambda},$$

would necessarily increase. But this implies that if (3.4) held initially, it would cease to hold after the increase in L . This reasoning implies that an increase in L must necessarily lead to

an increase in λ .

The intuition for this induced *competition effect* of increasing export market size, can be explained as follows: an increase in export market size L leads to an increase in the mass of products $N\hat{c}$ exported to country D (free entry condition 3.3); but then each individual exporting firm to country D will face a more elastic curve as it faces more competition from other exporting firms to D , which in turn corresponds to an increase in λ .⁶

Overall, an increase in export market size L induces both:

1. a *direct market size effect* which fosters innovation, more so for more productive firms;
2. an *induced competition effect* which discourages innovation, but less so for more productive firms, i.e. firms with lower \tilde{c} .

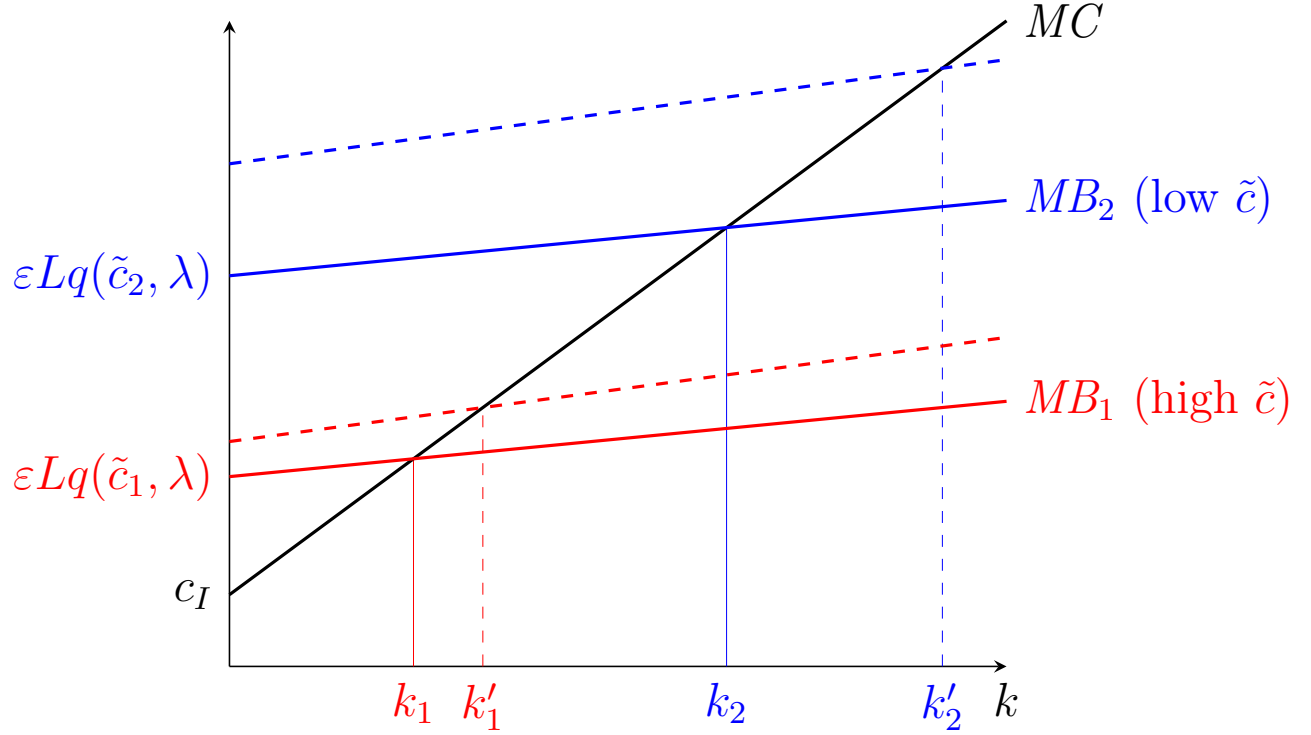
Figure 3.5 depicts the overall response of innovation to an increase in market size L . The slope unambiguously increases, but the intercept can increase or decrease depending on the relative strength of these two forces. On this graph, the market size impact dominates for the low cost firm (in blue), while the competition effect dominates for the high cost firm (in red). Indeed only the competition effect can explain reduced innovation in the wake of expanding export markets.

3.2.6 The effect of an increased share of country D 's consumption on French products

An increase in the share η_F of country D 's revenue spent on French products will result in a reduction of the competition variable λ . This immediately results from equation (3.4) together

⁶Another interpretation is that, as the number of products exported to country D increases, the representative consumer from country D gets a higher increase in utility for every extra dollar of income as she can increase consumption across a higher variety of products. This in turn implies that the marginal utility of income λ must increase.

Fig. 3.5: Overall response of innovation to an increase in market size L



with the fact that the function

$$r(c(\tilde{c}, \lambda), \lambda) = \frac{\alpha^2 - (C\lambda)^2}{4\beta\lambda},$$

is decreasing in λ so that the LHS of (3.4) is also decreasing in λ .

The induced effect will thus be to *encourage innovation, but less so for more frontier firms*.

Remark: A decrease in η_F will thus reinforce the competition effect of an increase in L : both will contribute to reduce innovation, and the more so for less frontier firms, i.e. for firms with higher baseline costs.

3.2.7 More general utility and R&D cost functions

All the intuitions and results highlighted above hold when we consider more general consumer utility, profit and R&D cost functions. The demand for differentiated varieties q_i on the export market is generated by L consumers who solve:

$$\max_{q_i \geq 0} \int u(q_i) di \text{ s.t. } \int p_i q_i di = 1.$$

(consumer expenditures on differentiated varieties normalized to 1)

So long as

$$\mathbf{(A1)} \quad u(q_i) \geq 0; \quad u(0) = 0; \quad u'(q_i) > 0; \quad \text{and } u''(q_i) < 0 \text{ for } x_i \geq 0,$$

this leads to the downward sloping inverse demand function (per consumer)

$$p(q_i, \lambda) = \frac{u'(q_i)}{\lambda}, \text{ where } \lambda = \int_0^M u'(q_i) x_i di > 0,$$

is the marginal utility of income (spent on differentiated varieties).

Then the optimal production and profits (per consumer) by a firm with marginal production cost c and facing market competition λ , be denoted respectively by $q(c, \lambda)$ and $\pi(c, \lambda)$,

$$\pi(c, \lambda) = \max_q L [p(q, \lambda)q - cq],$$

and

$$q(c, \lambda) = \arg \max_q L [p(q, \lambda)q - cq].$$

Note that $q(c, \lambda)$ is decreasing in c and in λ , a fact which we will use below.

Starting from baseline cost \tilde{c} , a firm that invests k in R&D reduces marginal cost down to $c = \tilde{c} + \psi(k)$, where $\psi'(k) \leq 0$. Especially because we allow for more general cost reduction

functions $\psi(k)$, without any major loss of insight here can restrict attention to the case of a quadratic innovation cost $c_I k + \frac{1}{2}c_{I2}k^2$.

Then a firm with baseline cost \tilde{c} chooses its optimal innovation investment $k(\tilde{c}, \lambda)$ so as to maximize $L\pi(\tilde{c} + \psi(k), \lambda) - c_I k - \frac{1}{2}c_{I2}k^2$. Let

$$\Pi(\tilde{c}, \lambda, k) = \pi(\tilde{c} + \psi(k), \lambda).$$

The first-order condition for the choice of optimal innovation investment is:

$$L \frac{\partial \Pi}{\partial k}(\tilde{c}, \lambda, k) = c_{I2}k + c_I. \quad (3.5)$$

We shall now make use of the fact that $k \rightarrow \Pi(\tilde{c}, \lambda, k)$ is supermodular with respect to the production cost \tilde{c} and also with respect to λ . That is,

$$\frac{\partial^2 \Pi}{\partial k \partial \tilde{c}} < 0,$$

and

$$\frac{\partial^2 \Pi}{\partial k \partial \lambda} < 0.$$

To see this, note first that by the envelope theorem we have:

$$\frac{\partial \Pi}{\partial k} = -Lq(c, \lambda)\psi'(k).$$

It then immediately follows that:

$$\begin{aligned} \frac{\partial^2 \Pi}{\partial k \partial \tilde{c}} &= -L \frac{\partial q(\tilde{c} + \psi(k), \lambda)}{\partial \tilde{c}} \psi'(k) < 0 \\ \frac{\partial^2 \Pi}{\partial k \partial \lambda} &= -L \frac{\partial q(\tilde{c} + \psi(k), \lambda)}{\partial \lambda} \psi'(k) < 0. \end{aligned}$$

Having established the supermodularity of the profit function $k \rightarrow \Pi(\tilde{c}, \lambda, k)$ with respect to \tilde{c} and λ , by Topkis’s Monotonicity Theorem (e.g. see Amir, 2005) we immediately get that the optimal R&D investment $k(\tilde{c}, \lambda)$ is decreasing in \tilde{c} and λ since $\frac{\partial q(\tilde{c}+\psi(k),\lambda)}{\partial \tilde{c}} < 0$ and $\frac{\partial q(\tilde{c}+\psi(k),\lambda)}{\partial \lambda} < 0$. Moreover, we can show that:

$$\frac{\partial^2 k}{\partial L \partial \tilde{c}} < 0.$$

Now by (3.5) an increase in market size L will have the direct effect of increasing the optimal R&D investment k for given \tilde{c} and λ : this is the *direct market size effect*. But in addition it will increase λ by the same reasoning as in the previous section, thereby reducing the optimal R&D investment: this is the *induced competition effect*. In all, investment in innovation increases more in response to an increase in market size in firms with lower baseline costs \tilde{c} .

3.3 Exporters and Innovators: data and descriptive statistics

In this section, we briefly present our datasets and show some descriptive evidence on the link between firms’ innovation and exports. Further details about data construction can be found in Appendix B.1.

3.3.1 Data sources

We build a database covering all French firms and linking export, fiscal and innovation data from 1994 to 2012. Our database draws from three sources: (i) French customs, which reports yearly export flows at a very disaggregated HS8 product level (representing over 10,000 manufacturing products) by destination; (ii) Insee-DGFIP administrative fiscal datasets (FICUS and FARE),

which provide extensive production and financial information for all firms operating in France; (iii) the Spring 2016 vintage of PATSTAT patent dataset from the European Patent Office, which contains detailed information on all patent applications from every patent office in the world. In our analysis we will focus on all patent applications (whether ultimately granted or not) but (see Appendix B.1 for details).

Although each French firm has a unique identifying number (Siren) across all French databases, patent offices do not identify firms applying for patents using this number but instead using the firm's name. We use the rigorous matching algorithm developed in [Lequien et al. \(in progress\)](#) to link each patent application (and its citations) back to the French firms' Siren numbers for all firms with more than 10 employees.

Finally, we use two additional datasets to construct measures of demand shocks across export destinations for French firms. CEPII's BACI database reports bilateral trade flows at the HS6 product level (covering more than 5,000 manufacturing products). IMF's *World Economic Outlook* provides country information such as GDP or GDP per capita.

Sample restrictions

Although our main firm-level administrative data source is comprehensive, with more than 47.1 million observations spanning over 7.3 million different firms from 1995 to 2012, we restrict our data sample for several reasons. The first is due to the matching with patent data mentioned above, which is most complete for firms above 10 employees. We therefore impose this size restriction, which drops a large number of firms but a relatively small share of aggregate French production: 17.1% of employment, 15.6% of sales, and 13.6% of exports (predominantly within EU exports). Second, we restrict our attention to private firms (legal category 5 in the Insee classification). We thus drop state-owned firms, self-employed businesses, non-profit organizations, as we focus on profit-maximizing firms. This further reduces our sample from

1.7 million to 835,000 firms. Yet, the bulk of aggregate employment (74.2%), sales (77.7%), and exports (77.2%) remain in our dataset after imposing these restrictions. These remaining firms are matched with an average of 27,640 patents per year in PATSTAT. Lastly, since our detailed customs trade data only covers goods trade (and not services), we will further restrict our sample to the manufacturing sector for most of our analysis.⁷ This reduces our working sample to 105,000 firms. Nevertheless the bulk of French aggregate exports and innovation are still concentrated in manufacturing: only 20.6% of aggregate exports and 33% of patents are recorded outside of the manufacturing sector.

3.3.2 Sector breakdown and skewness

Table 3.1 shows the breakdown of those firms across sectors, along with their average employment, exports, and patents (per firm) for 2007.⁸ As has been widely reported in the empirical literature on micro-level trade patterns, many firms are only occasional exporters: they export in some years, but not in others. This pattern is even more pronounced for innovation: even firms with substantial ongoing R&D operations do not typically file patent applications year in and year out. We therefore use the broadest possible cross-year definition to classify firms as exporters and innovators. We label a firm as an *exporter* if it has exported at least once between 1993-2012; and as an *innovator* if it has filed at least one patent application between 1995-2012.⁹ Thus, our reported export participation rates in Table 3.1 are higher than in other studies. However, even with this broadest classification, innovators represent only a small minority of manufacturing firms. For comparison, Table 3.1 also reports the share of exporters and

⁷Although the customs data also covers the wholesale sector, we also exclude those firms as they do not produce the goods that they export.

⁸Throughout, we define sectors at the 2-digit level of the NAF rev2 classification. We also eliminate the tobacco sector (# 12) as it only contains two firms.

⁹The initial year for both ranges do not coincide so as to best reflect our subsequent empirical analyses. We will use prior years of export data to construct exogenous export share weights (see section 3.4.1 for more details).

innovators based on the more standard definition of current year (2007 for this table) exporting or patenting activity – shown in parentheses.

Table 3.1: Exports and innovation in the manufacturing sector

Sector	Description	Firms	Emp	Export	% Exporter	Patents	% Innov.
10	Food products	8,764	43	1,856	41 (26)	0.020	2 (0)
11	Beverages	1,452	47	5,974	80 (59)	0.012	2 (0)
13	Textiles	1,802	37	2,335	86 (63)	0.106	12 (2)
14	Wearing apparel	1,558	39	2,577	80 (59)	0.065	5 (1)
15	Leather	492	56	2,566	85 (59)	0.090	9 (2)
16	Wood	2,432	29	790	63 (36)	0.017	5 (1)
17	Paper	2,950	44	2,056	79 (44)	0.086	7 (1)
18	Printing	842	24	167	52 (20)	0.006	3 (0)
19	Coke	171	225	75,957	92 (69)	3.883	22 (9)
20	Chemicals	1,229	116	17,607	94 (79)	2.347	21 (7)
21	Basic pharmaceutical	357	288	42,065	96 (82)	3.282	35 (13)
22	Rubber and plastic	2,745	80	3,820	86 (64)	0.398	21 (6)
23	Other non-metallic	2,158	63	2,320	65 (38)	0.363	11 (2)
24	Basic metals	1,648	80	12,487	65 (44)	0.176	11 (3)
25	Fabricated metal	8,392	36	1,125	67 (40)	0.091	9 (2)
26	Computer and electronic	3,511	85	7,602	72 (54)	0.949	23 (8)
27	Electrical equipment	447	106	8,812	91 (70)	2.095	26 (8)
28	Machinery and equipment	4,668	80	8,252	79 (58)	0.584	23 (7)
29	Motor vehicles	791	61	2,549	79 (47)	0.200	15 (3)
30	Other transport equipment	558	215	54,910	83 (56)	2.555	18 (7)
31	Furniture	1,146	34	598	67 (36)	0.031	7 (1)
32	Other manufacturing	1,017	41	2,472	82 (58)	0.392	12 (3)
33	Repair and installation of machinery and equipment	3,430	28	302	54 (23)	0.029	6 (1)
	Aggregate manufacturing	52,621	56	4,634	68 (44)	0.335	11 (3)

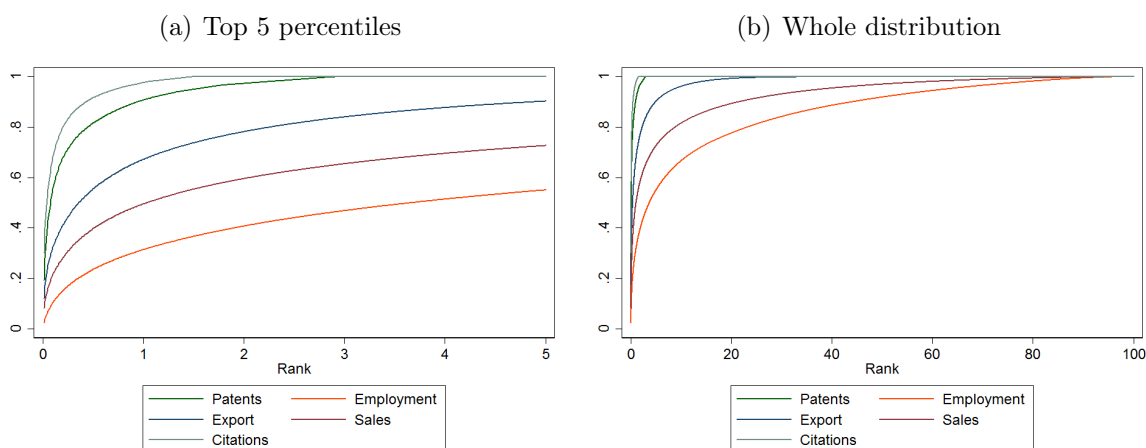
Notes: This table presents the number of firms, average employment, average export (in thousands of Euros), average number of patents, and the shares of exporters and innovators (cross-year definitions). The shares in parentheses are calculated based on current year export participation or patent filing. Data are for 2007.

Even within the minority set of innovators, patenting activity is extremely skewed. This is clearly visible in Figure 3.6, which plots the Lorenz curve for manufacturing patents in 2007, along with the Lorenz curves for exports, sales, and employment. Figure 3.6 confirms the previously reported finding that firm-level exports are significantly more skewed than sales and employment (e.g. see Mayer et al., 2014 and Bernard et al., 2016): The top 1% of exporters

account for 67% of aggregate exports in 2007, whereas the top 1% of firms based on total size account for 50% of sales (ranked by sales) and 31% of employment (ranked by employment). But Figure 3.6 also shows that patenting is even significantly more skewed than exporting: the top 1% of patenting firms account for 91% of patents in 2007 and 98% if we weight patents by the number of citations they receive. Indeed fewer than 2.9% of manufacturing firms have patented in 2007. This fraction is significantly smaller than our previously reported 11% share of innovators in Table 3.1 measured across our full sample years. Similarly, only 44% of manufacturing firms report any exporting activity for 2007 compared to a 68% share when exporting is measured across our full sample years.

These univariate statistics for patenting and exporting do not capture the massive overlap between these two activities across firms – which we investigate in more detail below.

Fig. 3.6: Lorenz curves - patents are more concentrated than exports, sales and employment



Notes: Lorenz curves plot cumulative distribution function for patents, triadic patents, employment, export and sales. Data are for manufacturing firms.

3.3.3 The innovation-export nexus

Looking across our sample years (1995-2012), Table 3.2 reports different size-related performance measures (averages per firm) based on their exporter and innovator classification. This

table confirms the well-documented size differential in favor of exporters. However, several new salient features regarding innovators pop-out from this table: 1) Innovating firms are massively concentrated among exporters: only 5% of innovators do not report any exporting. 2) Those non-exporting innovators do not look very different than their non-innovating counterparts amongst non-exporters. All the various measures of firm size (employment, sales, value-added) are within ten percent of each other.¹⁰ 3) On the other hand, the size differences between innovators and non-innovators amongst exporters are massive: innovators employ on average 4.5 times more workers and produce 7-8 times more output and value-added than non-innovating exporters. They export almost 10 times more than non-innovators and reach more than three times the number of export destinations. These size differentials are many multiples larger than those separating exporters and non-exporters. In the aggregate, this small subset of innovators accounts for over half of French manufacturing exports.

We now examine these performance differentials in favor of exporters and innovators in greater detail. We first focus on the exporter premia in the top panel of Table 3.3. These premia are generated by regressing the performance measure of interest (listed in the rows) on our exporter indicator – with each cell representing a separate regression. Column 1 includes no other controls; Column 2 adds a 2-digit sector fixed effect (see Table 3.1); and Column 3 also controls for firm employment, in addition to the sector fixed effect. Since we are using a broad cross-year definition for exporter status, we expect these premia to be lower than measures based on current-year exporter status.¹¹ This is the case for the premia in column 1 compared to similar number reported by Bernard et al. (2016) for U.S. firms in 2007. Yet, once we control for sectors in column 2, the reported premia are much more similar. In particular, we verify that

¹⁰This is not the case outside of the manufacturing sector. In those other sectors, non-exporting innovators are substantially bigger than their non-exporting and non-innovating counterparts. We conjecture that this is driven by the fact that exporting no longer serves the same performance screening function outside of manufacturing. See Table B.1 in Appendix B.2.

¹¹Since firms who drop in and out of export markets tend to be substantially smaller than year in year out exporters.

Table 3.2: Exporters and innovators are bigger

	Non-exporters		Exporters		Total
	Non-innovator	Innovator	Non-innovator	Innovator	
Firms	45,707	385	51,221	6,770	104,083
Employment	17	21	52	235	59
Sales	2,173	2,530	11,671	69,906	14,075
Value Added	646	908	2,775	16,242	3,354
Age	14	15	20	22	18
Exports	0	0	2,440	23,155	3,622
Countries	0	0	5	18	5
Patents	0	0.2	0	2.6	0.3

Notes: This table presents basic descriptive statistics across four categories of manufacturing firms whether they innovate, export, both or none. Employment is given in full-time equivalent on average over the year and exports, sales and value added are in thousand of euros. Countries is the number of destination countries for exports. Employment, Sales, Value Added, Age, Exports, Countries and Patents are taken as a yearly average over the whole period 1995-2012.

even within sectors, exporters are substantially larger than non-exporters. And we also find that large differences in productivity and wages in favor of exporters persist after controlling for firm employment (within sectors).

In the bottom panel, we focus on the subset of exporters from the top panel, and report the *additional* premia in favor of innovators within this subset. As with the top panel, those premia are calculated by running separate regressions on our innovator indicator. Even within this subset of bigger and better performing firms, innovators stand out: they are substantially bigger, more productive, and pay higher wages. They also export substantially more (and to more destinations) than non-innovative exporters. All these differences persist within sectors and controlling for firm employment.

Even these large premia do not characterize the concentration of innovative and exporting activities within an even more restricted subset of exporters and innovators. To capture this

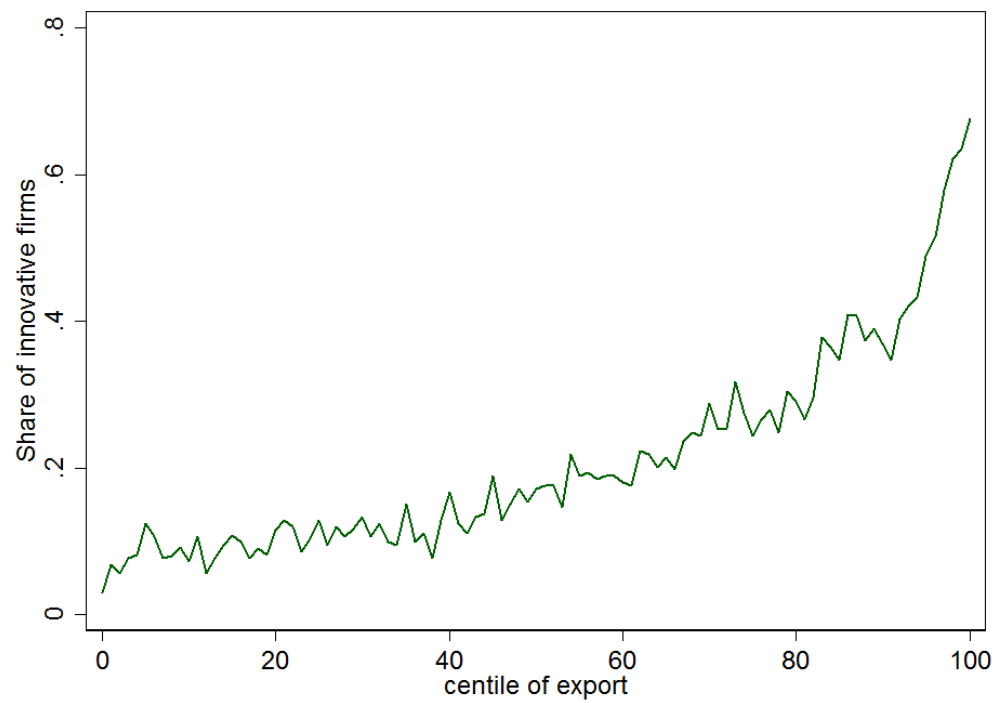
Table 3.3: Export and innovation premia

Panel 1: Premium for being an exporter (among all manufacturing firms)					
	(1)	(2)	(3)	Obs.	Firms
log Employment	0.851	0.762	-	931,309	90,688
log Sales	1.613	1.474	0.417	972,956	103,404
log Wage	0.132	0.097	0.110	929,756	90,653
log Value Added Per Worker	0.217	0.171	0.176	918,062	90,055
Panel 2: Premium for being an innovator (among all exporting manufacturing firms)					
	(1)	(2)	(3)	Obs.	Firms
log Employment	1.038	0.993	-	639,938	57,267
log Sales	1.277	1.233	0.197	650,0134	57,901
log Wage	0.15	0.095	0.110	638,955	57,253
log Value Added Per Worker	0.203	0.173	0.180	629,819	56,920
log Export Sales (Current period exporters)	2.043	1.970	0.859	433,456	56,509
Number of destination countries	13	12	7	656,609	57,991

Notes: This table presents results from an OLS regression of firm characteristics (rows) on a dummy variable for exporting (upper table) or patenting (lower table) from 1994 to 2012. Column 1 uses no additional covariate, column 2 adds a 3-digit sector fixed effect, column 3 adds a control for the log of employment to column 2. All firm characteristic variables are taken in logs. All results are significant at the 1 percent level. Upper table use all manufacturing firms whereas lower table focuses on exporting manufacturing firms.

concentration at the “intensive” margin of firm-exports, Figure 3.7 plots the share of innovating firms for each centile of the firm export distribution. We see that the innovative firms are highly concentrated within the top percentiles of the export distribution. At the 80th percentile of the export distribution, 30% of the firms have some patenting experience. And the increase in the share of innovative firms with the percentile of the export distribution is convex. Above the 95th percentile of the export distribution, a majority of firms are innovators; in the top percentile, 68% of the firms are innovators. Those firms in the top export percentile account for 41% of the aggregate share of French patents.

Fig. 3.7: The share of innovators jumps at the top of the export distribution



Notes: Centiles of exports are computed each year from 1995 to 2012 separately and then pooled together. For each centile, we compute the share of innovators. Each centile contains the same number of firms, except for centile 0 that contains all the firms with no export.

3.4 Empirical framework and results

3.4.1 Identification strategy: firm-level export shocks

We have just documented the strong correlation between exporting and innovation in the cross-section of French manufacturing firms. This correlation does not shed light on the direction of causation: from innovation to exports (a brilliant innovation leads to growth in export demand and entry into new export markets), or from exports to innovation (as our theoretical model explains). In addition, other firm-level changes could generate concurrent changes in both innovation and exports (for example, a new management team). Thus, to identify the causal relationship from exports to innovation, we need to identify a source of variation in firm exports that is exogenous to changes within the firm (and in particular to innovation activity at the firm). We follow [Mayer et al. \(2016\)](#) in building such a measure of exogenous export demand (to the firm).

Consider a French exporter f who exports a product s to destination j at an initial date t_0 . Let X_{fst_0} denote this export flow, where t_0 is the firm's first observed export year in our sample.¹² The underlying idea is that subsequent changes in destination j 's imports of product s from the world (excluding France) will be a good proxy for the change in export demand faced by this firm. Let M_{jst} denote this trade flow into j at time $t > t_0$. By excluding French exports to this destination, we seek to exclude sources of variation that originate in France and may be correlated with changes for the firm.¹³ We construct our exogenous export demand shock for firm f at time t by averaging the world export flows M_{jst} across destinations j and products s

¹²We consider this firm to be an exporter only if we observed positive exports in our customs data (so we can calculate destination market shares) as well as in our production/administrative data (so we can calculate export intensity).

¹³Later, we will also exclude firms with dominant market shares in any destinations.

using firm f 's market shares at the initial date t_0 :

$$D_{ft}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst}. \quad (3.6)$$

The weights $(X_{ft_0}^*/S_{ft_0}^*)(X_{fjst_0}/X_{ft_0})$ represent firm f 's initial share of sales of product s to destination j . $X_{ft_0} = \sum_{j,s} X_{fjst_0}$ represents the firm's total exports. In order to incorporate firm f 's sales to its domestic French market, we scale the firm's export share X_{fjst_0}/X_{ft_0} by its export intensity $X_{ft_0}^*/S_{ft_0}^*$, where $X_{ft_0}^*$ and $S_{ft_0}^*$ denote the firm's total exports and total sales taken from the production data. We use asterisks to denote that these data come from a different source than the customs data used to calculate the export shares.¹⁴

We note that the time variation in our demand shock $D_{ft}^{M_s}$ only stems from the world export flow M_{jst} and not the firm-level weights, which are fixed in the initial export period t_0 . We expect that a firm's innovation response at time $t > t_0$ will induce changes to its pattern of exports at time t and beyond, including both intensive margin responses (changes in exports for a previously exported product s to a destination j) and extensive margin responses (changes in the set of products s sold across destinations j). By fixing the firm-level weights in the initial period t_0 (including the extensive margin set of products and destinations), we exclude this subsequent endogenous variation from our demand shock. In order to ensure that the time variation in the world export flow M_{jst} is not influenced by time $t > t_0$ decisions made by dominant French exporters in market (j, s) (including, most importantly, their innovation decisions), we will investigate excluding those firms from our analysis (see appendix 3.4.4.2).

We will also experiment with alternate measures of this demand shock using more aggregated data (across products). First, we aggregate both the world and the firms' export shares at the

¹⁴Total exports reported by customs and in the production data do not always exactly match, though they are very highly correlated.

3-digit ISIC level:

$$D_{ft}^{M_I} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,I} \frac{X_{fjIt_0}}{X_{ft_0}} \log M_{jIt},$$

where $M_{jIt} = \sum_{s \in I} M_{jst}$ measures aggregate imports (excluding France) in destination j for industry I , and $X_{fjIt_0} = \sum_{s \in I} X_{fjst_0}$ is the associated firm-level exports for that industry-destination pair in the initial year t_0 . This measure will no longer reflect the cross-firm variation at the detailed product level. However, it captures some potential spillovers across related products in the construction of the demand shock (an increase in export demand for closely related products may induce a firm to direct innovation towards these related products). Lastly, at the most aggregate level for a destination j , we will measure changes in GDP (at current exchange rates), and weight those with the firms' export shares in those destinations:

$$D_{ft}^G = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_j \frac{X_{fjt_0}}{X_{ft_0}} \log GDP_{jt},$$

where $X_{fjt_0} = \sum_s X_{fjst_0}$ represents the firm's initial exports to destination j . One benefit of this aggregation is that it allows us to incorporate the domestic response to demand in destination j .

The construction of these export demand shocks generates some outliers for a few firms who export just a few products to small destinations (such as yachts to Seychelles and Maldives). We therefore trim from our sample the firms with extreme changes in the export demand variable. We regress the firm demand shock on a firm fixed effect and trim observations with a residual that is above/below the 97.5th/2.5th percentile of that distribution. Thus, observations with the largest variations in their export demand shock (relative to their firm mean) are eliminated.¹⁵

¹⁵The incidence of these outliers decreases as we aggregate the trade flows from products to industries, and then switch from industries to destination GDP. We have experimented with different threshold cutoffs in the 0-5% range. Our qualitative results are robust to these changes and coefficient estimates are essentially unaffected by these changes after 1%. See Table B.2 in Appendix B.2.

3.4.2 Estimation

Our baseline regression seeks to capture the impact of the exogenous demand shock on a firm’s innovation response. We expect this innovation response to be sluggish and incorporate the accumulated effects of the trade shocks over time. We therefore start with an estimation in levels (log-levels for the trade shock) focusing on the within-firm response by incorporating firm fixed-effects. We also add sector-time dummies to capture any sector-level changes over time.

For now, we restrict our analysis to the subset of innovating firms. We will separately investigate the entry margin into the set of innovating firms (a first patent after 1994).¹⁶ We measure their innovation output Y_{ft} at time t using their number of patent applications during year t . We will also alternatively restrict our count to triadic patents. Given our estimation strategy with firm fixed-effects, we seek to capture changes in this number of applications over time (driven by the introduction of additional new patents).

In order to capture the indirect competition effect of an export demand shock (which varies with a firm’s productivity level), we add an interaction between the demand shock and firm productivity. Just as we did with the firm-level export shares, we only use our initial year t_0 to generate a productivity measure that does not subsequently vary over time $t > t_0$.¹⁷ We assign a 0-9 productivity index d_f to all firms based on their labor productivity (value-added per worker) decile in year t_0 within their 2-digit sector.¹⁸

We thus estimate the following model:

$$Y_{ft} = \alpha D_{ft}^{M_s} + \beta D_{ft}^{M_s} * d_f + \chi_{s,t} + \chi_f + \varepsilon_{ft}, \quad (3.7)$$

¹⁶Our theoretical model highlights that the “entry” decision into innovation in response to an export demand shock will likely have a very different functional form: only the set of firms “close-enough” to the innovation threshold will start innovating in response to a positive demand shock.

¹⁷Recall that t_0 is the first year since 1994 in which the firm reports positive exports. This year is most of the time equal to 1994 and is always removed from the estimation.

¹⁸When a firm belongs to the manufacturing sector for a subset of our sample years, we only use those years in our estimation. For a firm not in our manufacturing sample at t_0 , we compute its productivity decile within its previous sector at t_0 .

where Y_{ft} is the number of patent applications during year t by firm f and $D_{ft}^{M_s}$ is one of our demand measure described in Section 3.4.1 built to be exogenous to the firm’s decision.¹⁹ The $\chi_{s,t}$ and χ_f capture the sector-time and firm fixed effects and ε_{ft} is an error term. In most of our regressions, we will estimate coefficients and standard errors of equation (3.7) using a Newey-West estimator for the covariance matrix which allow for heteroskedasticity and autocorrelation in the error terms with a maximum lag of 5 years (see Newey and West, 1987 and Wooldridge, 2010).²⁰

3.4.3 Baseline results

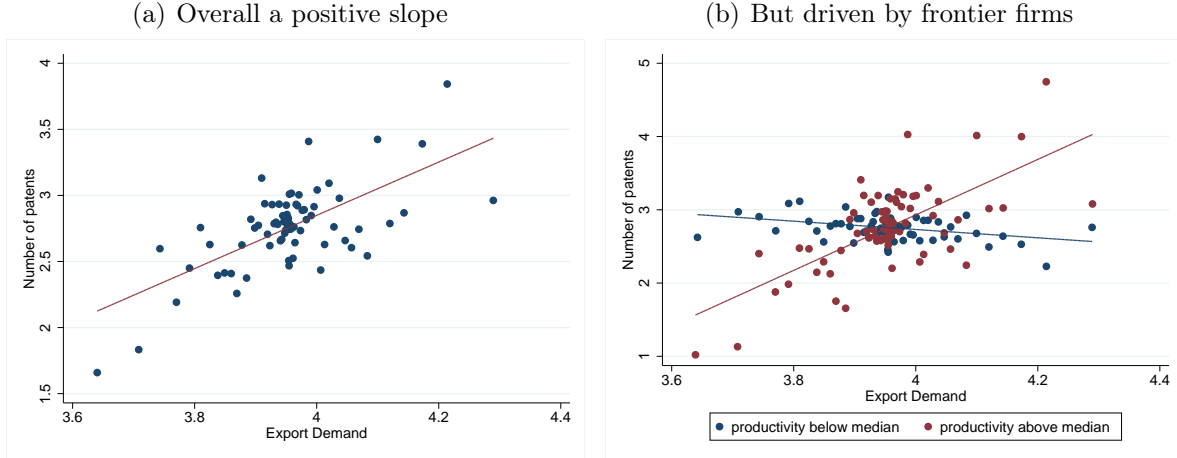
Our model in Section 3.2 predicts that an increase in market size should have both a positive market size effect and a counteracting competition effect which is most pronounced (and potentially dominant) for the least productive firms (section 3.2.5). Figure 3.8 shows that a firm’s patenting responds much more strongly to export demand for manufacturing firms that are initially more productive (a productivity decile d_f above the median) although the overall effect is positive.

This response of innovation to demand conditions differs markedly between the two groups of firms based on their initial productivity. Our regressions results strongly confirm this qualitative pattern, and show that it is robust to alternative measures of innovation, productivity, demand conditions, and the timing of our sample. The results from our baseline estimation of (3.7) using all three versions of our export demand shocks (different aggregation levels across products) and our two main measures of innovation output (all patent applications and triadic patent

¹⁹One potential critic on the exogeneity of this variable is that more productive and innovative firms can better anticipate markets that will increase in the future. As t_0 is most of the time equal to 1994 and since we estimate our coefficient over the 1995-2012 time period, we argue that it is unlikely that a firm can predict that far in time. To reinforce this, we show in Table B.3 in Appendix B.2 that removing the first years following t_0 does not qualitatively affect our results.

²⁰We also show robustness of our baseline results using standard errors clustered by firm (see Table B.4 in Appendix B.2). However, given the relatively long time dimension of our sample, we believe this specification is too demanding and prefer the Newey-West estimator.

Fig. 3.8: Patenting increases more with demand for initially more efficient firms



Notes: Each dot represents the quantile-average of the residual of the number of patent on a firm fixed effect (y-axis) against the quantile-average of the residual of the demand variable D_{ft}^{Ms} on a firm fixed effect (x-axis), for firms below (blue) or above (red) the productivity median at t_0 .

applications) are presented in table 3.4. This table clearly shows that initially more productive firms respond to an export demand shock by innovating relatively more. For firms in the lowest productivity decile ($d_f = 0$), we see that the effect of the export shock is strongly negative: a positive export shock induces those firms to introduce fewer patents relative to the sector average for that year. In all cases, the effect of the export shock is reversed and strongly positive for all firms above a productivity decile.

Our results from column (1) using the product-level demand shock imply the following quantitative response in the number of patents: for a firm in the lowest productivity decile, the number of patents (relative to the firm average) is 3.3 patents lower than the sector average; each additional productivity decile increases this patent response by 0.96 patent; and thus for a firm in the top decile of productivity, the number of patents is 8.7 larger than the sector average (still relative to the firm average). Our results using the more aggregated demand shocks (columns 2 and 3), or restricting to triadic patents (columns 4 to 6) yield very similar results.

Table 3.4: Baseline results

Dependent variable	Number of patents			Number of triadic patents		
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_I}$ (2)	D_{ft}^G (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_I}$ (5)	D_{ft}^G (6)
Demand	-3.269*** (1.014)	-2.585** (1.056)	-3.037** (1.466)	-0.868*** (0.265)	-0.816** (0.360)	-0.851* (0.450)
Decile \times Demand	0.962*** (0.255)	0.911*** (0.304)	0.852** (0.394)	0.222*** (0.060)	0.176** (0.083)	0.304** (0.124)
Nb of observation	77,901	77,918	77,002	77,901	77,918	77,002
R ²	0.905	0.897	0.901	0.895	0.889	0.884

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

The innovation response to an increasing export demand can be tested using different patent indicators. This is what Table 3.5 do using three other measures, in addition to counting all patents and restricting to triadic applications (columns 1 and 2 respectively). Thus, column 3 count only prior applications, column 4 only count granted patent applications and column 5 count the number of patent families.²¹ These different measures help to correct for potential bias that could arise from heterogeneity in patent offices legislation, across space and sectors. Reassuringly, results are qualitatively unchanged regardless of the indicator we use.

3.4.4 Additional results

Our main finding – that initially more productive firms respond to an export demand shock by innovating relatively more – is robust to many alternative specifications. In this subsection, we show the robustness of our main results to: (i) adding controls for firm size; (ii) excluding dominant firms in a destination market; (iii) changing the way we identify frontier firms; and

²¹The exact definition and construction of these measures from PATSTAT can be found in Appendix B.1

Table 3.5: Other patent indicators

Dependent variable	All	Triadic	Prior	Only granted	Families
Demand Measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)
Demand	-3.269*** (1.014)	-0.868*** (0.265)	-1.366*** (0.502)	-1.201* (0.629)	-2.788*** (0.776)
Decile \times Demand	0.962*** (0.255)	0.222*** (0.060)	0.409*** (0.133)	0.364** (0.155)	0.772*** (0.204)
Nb of observation	77,901	77,901	77,901	77,901	77,901
R ²	0.905	0.895	0.844	0.908	0.878

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

(iv) adding productivity decile specific time-trends. Various other robustness checks are shown in Appendix B.2.

3.4.4.1 Controlling for size effect

We now control directly for the potential impact of other structural changes within firms. A firm in the midst of a growth spurt (not initially related to innovation) may respond to this increase in scale by innovating and exporting more (nevertheless, there is no strong reason why the firm-level growth spurt would be correlated with the export demand shock). Also, a potential confounding effect for our competition channel is that initially less productive firms may anticipate lower sales responses from a given demand shock – relative to initially more productive firms (although, by construction, our demand shock is independent of overall firm size). To assess the relevance of these channels, we directly control for firm size (at time t) in our baseline regression. We select different empirical measures of size: employment, raw materials, net and gross capital stock, and sales. The corresponding regression results are reported in

Table 3.6 (see also Table B.5 in Appendix B.2 for similar results using only triadic patents). They clearly show that a direct control for size does not affect our previously reported baseline coefficients (reported again in column 1): the coefficients remain virtually unchanged.

Table 3.6: Control for firm size

Dependent variable	Number of patents					
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_s}$ (6)
Demand	-3.269*** (1.014)	-3.436*** (1.039)	-3.286*** (1.024)	-3.220*** (1.017)	-2.807*** (1.004)	-3.288*** (1.012)
Decile \times Demand	0.962*** (0.225)	0.971*** (0.263)	0.954*** (0.257)	0.960*** (0.256)	0.876*** (0.258)	0.977*** (0.255)
Size		0.603*** (0.114)	0.696*** (0.096)	1.257*** (0.201)	2.007*** (0.350)	1.227*** (0.187)
Nb of observation	77,901	76,236	76,678	76,860	77,240	77,605
R ²	0.905	0.908	0.906	0.906	0.906	0.906

Notes: This table presents regression results of an OLS estimation of equation 3.7 where we add a control for firm size. Column 1 uses no control, column 2 controls for the log of raw material inputs, column 3 (resp. 4) controls for the log of net (resp. gross) capital stock, column 5 controls for the log of employment and column 6 controls for the log of sales. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

3.4.4.2 Excluding markets where a firm is a leader

If a firm has a dominant market share in a market (j, s) , then the world exports M_{jst} may be correlated with the firm's exports X_{fst} (even though French exports are excluded from the construction of the world exports M_{jst}). To investigate this further, we drop from our dataset the markets (j, s) (in all years) for a firm f whenever its export sales in market (j, s) are above 10% of world exports (including France) into this market for any given year. These instances represent 6.7% of the customs data observations and essentially concern firms exporting in

African countries. The results are reported in Table 3.7 which should be compared to Table 3.5; and once again leave our baseline results virtually unchanged.

Table 3.7: Excluding leaders

Dependent variable	All	Triadic	Prior	Only granted	Families
Demand Measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)
Demand	-2.820*** (0.970)	-0.804*** (0.268)	-1.058** (0.464)	-0.664 (0.589)	-2.478*** (0.734)
Decile \times Demand	0.766*** (0.239)	0.187*** (0.064)	0.318*** (0.118)	0.213 (0.151)	0.640*** (0.184)
Nb of observation	77,790	77,790	77,790	77,790	77,790
R ²	0.905	0.903	0.839	0.909	0.873

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). The Demand variable does not include country j and products s for a firm f with a market share above 10% for the pair (j, s) . Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

3.4.4.3 Different measure of frontier firms

So far, our model uses initial productivity deciles to measure the heterogenous response of firms to an increasing export demand with regarding how much they are at the technological frontier. Here, we slightly alter this model and show robustness to using alternative identification of frontier firms. Table 3.8 shows that our baseline results (see column 1) are robust to measuring productivity deciles using sales over value added (column 2) or to splitting firms into two categories regarding their position in the initial productivity distribution (in the top 50%, 75%, 90% and 95%, respectively in columns 3, 4, 5 and 6).²² Results are consistent with our baseline using productivity decile, namely that the effect of the demand variable is positive for firms

²²Here again, similar results can be found using triadic patent applications, see Table B.7

that are above the median in terms of productivity, but seems to be very large for firms in the very top of the distribution.

Table 3.8: Alternative definition of frontier

Dependent variable	Number of patents					
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_s}$ (6)
Demand	-3.269*** (1.014)	-1.316 (0.890)	-5.480*** (1.349)	-0.090 (0.680)	0.520 (0.699)	0.578 (0.671)
Interaction	0.962*** (0.255)	0.578** (0.235)	4.438*** (1.117)	5.456*** (1.835)	8.375** (3.570)	16.63** (7.276)
Nb of observation	77,901	77,901	77,901	77,901	77,901	77,901
R ²	0.905	0.905	0.905	0.905	0.905	0.906

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Variable interaction is defined as the product of our demand variable and a variable capturing the frontierness of the firm. Column 1 is our baseline model, column 2 uses productivity deciles using sales over employment instead of value added over employment, columns 3 to 6 no longer construct decile groups but use a dummy variable for being above the 50th, 75th, 90th and 95th percentile of the initial productivity distribution. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

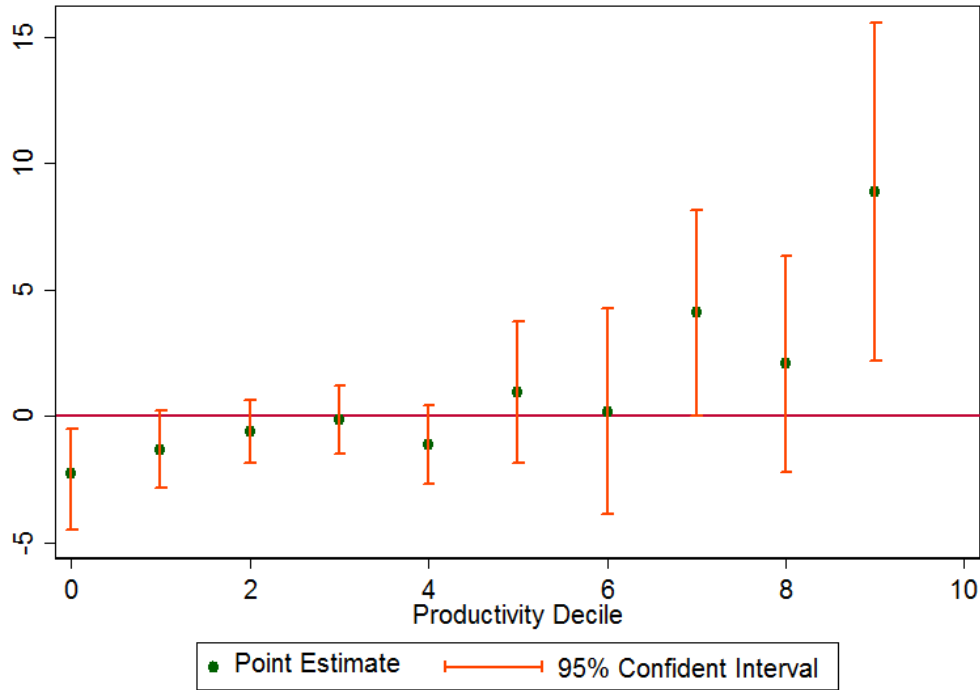
To confirm this result, we change our specification again and allow our key interaction coefficient β in equation (3.7) to vary with the productivity decile d_f . Our estimating equation then becomes:

$$Y_{ft} = \sum_{d=0}^9 [\beta_d D_{ft} * \mathbb{1}_{d_f=d}] + \chi_{s,t} + \chi_f + \varepsilon_{ft}, \quad (3.8)$$

where $\mathbb{1}_{d_f=d}$ are indicator dummies for each productivity decile. This new specification allows us to relax the assumption that there is a constant slope shift across decile groups and to account for potential non linear effects of our export demand shock variable for different levels of productivity. Coefficients and corresponding confident interval are graphically reported in Figure 3.9. They suggest that the assumption of a constant effect across decile group is a correct approximation, although the effect seems to be non-linear and to be concentrated in

the last decile (this confirms results of Table 3.8. This figure also highlights that the effect of the demand shock is clearly negative for some of the lowest productivity deciles; and that this effect turns positive for all deciles above the median (deciles 5 through 9).

Fig. 3.9: Response to Demand by decile of productivity



Notes: Regression coefficients and corresponding 95% confident intervals, constructed with Newey-West estimated standard errors of equation (3.8).

3.4.4.4 Control for productivity decile specific evolution

Our last robustness check consider the intuitive idea that firms in different initial productivity decile groups can be different in various dimension. Some of these dimensions are observable (size, export intensity...) and other are not (organization, quality of management...). To control for this, we add in our model presented in equation (3.7) fixed effect for each productivity decile and year. Results are shown in Table 3.9 and although the precision of the point estimates has

decreased, our results still hold.²³

Table 3.9: Control for productivity specific trend

Dependent variable	Number of patents			Number of triadic patents		
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_I}$ (2)	D_{ft}^G (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_I}$ (5)	D_{ft}^G (6)
Demand	-2.876*** (0.975)	-2.480*** (1.137)	-1.459 (1.584)	-0.762** (0.359)	-0.929** (0.449)	-0.647 (0.610)
Decile \times Demand	0.900*** (0.267)	0.921*** (0.340)	0.538 (0.462)	0.251** (0.098)	0.331** (0.132)	0.578*** (0.178)
Nb of observation	77,901	77,918	77,002	77,901	77,918	77,002
R ²	0.906	0.897	0.901	0.855	0.854	0.850

Notes: This table presents regression results of an OLS estimation of equation 3.7 to which a productivity decile \times year fixed effect is added. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

3.4.5 Additional results

In this last section, we show additional results that support our model.

3.4.5.1 Direct competition effect

To test more directly the competition effect that we highlight in the model, and to give support that the “demand-side” effects that we stress in the theory (as opposed to the shape of the innovation-cost-return function) are an important driver of the positive interaction terms found in previous regression, we rely to data computed in Djankov et al. (2002) and subsequently updated. This dataset associate each country in the world with a rating from 0 to 100 according to how easy it is to open a business in this country (0 corresponds to impossible). This provides

²³A similar table using productivity decile groups specific time trends can be found in Table B.6 of Appendix B.2

a more direct measure of innovation that we will use to construct two new demand shocks $D_{ft,A}^{M_s}$ and $D_{ft,B}^{M_s}$ according to:

$$D_{ft,A}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \mathbb{1}_{C_j > \hat{C}} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst},$$

and

$$D_{ft,B}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \mathbb{1}_{C_j \leq \hat{C}} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst},$$

where C_j denotes the value for the ease of doing business as reported by [Djankov et al. \(2002\)](#) and \hat{C} is the median of this value. Hence $\mathbb{1}_{C_j \leq \hat{C}}$ is equal to 1 if country j is less competitive than the median country. These two new demand variables sum up to our baseline measure $D_{ft}^{M_s}$ and capture respectively the size of the export markets from competitive countries and less competitive countries.

We then estimate the following model:

$$Y_{ft} = \alpha_A D_{ft,A}^{M_s} + \beta_A D_{ft,A}^{M_s} * d_f + \alpha_B D_{ft,B}^{M_s} + \beta_B D_{ft,B}^{M_s} * d_f + \chi_{s,t} + \chi_f + \varepsilon_{ft}, \quad (3.9)$$

where we expect β_A and α_A to behave as in equation (3.7) and β_B to be insignificant (or at least weaker than β_A) and α_B to be positive and capture all the market size effect. Results are presented in Table 3.10 where we have used different definition of frontier firms and either all patents or triadic patents. They are in line with what we expected and with the model, providing additional support in favor of the coexistence of both a market size and a competition effects.

Table 3.10: Direct measure of competition

Dependent variable	Number of patents			Number of triadic patents		
	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$	$D_{ft,A}^{M_s}, D_{ft,B}^{M_s}$
Definition of frontier	Baseline (1)	Above Median (2)	Above 75% (3)	Baseline (4)	Above Median (5)	Above 75% (6)
Demand (low comp.)	1.390 (3.437)	-5.819 (6.543)	6.475** (2.711)	-0.112 (1.026)	-3.718* (2.204)	3.079*** (1.075)
Demand (high comp.)	-4.775*** (1.602)	-6.670*** (2.204)	-0.992 (1.206)	-1.031** (0.408)	-1.693*** (0.603)	-0.365 (0.460)
Interaction (low comp.)	0.363 (1.003)	5.915 (5.396)	-10.15 (7.856)	0.487* (0.279)	3.834** (1.786)	-2.549 (2.138)
Interaction (high comp.)	1.335*** (0.437)	5.392*** (1.996)	9.683*** (3.229)	0.233** (0.091)	1.146** (0.559)	1.762** (0.748)
Nb of observation	74,646	74,646	74,646	74,646	74,646	74,646
R ²	0.909	0.909	0.909	0.904	0.904	0.904

Notes: This table presents regression results of an OLS estimation of equation (3.9). Demand (low comp.) corresponds to $D_{ft,B}^{M_s}$ as defined in section 3.4.5.1 and Demand (high comp.) to $D_{ft,A}^{M_s}$. Definition of the interaction uses the baseline productivity decile in columns 1 and 4, a dummy for being above median in terms of initial productivity in columns 2 and 5 and a dummy for being above the top 75% more productive firms in the initial period in column 3 and 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

3.4.5.2 Response of other variables

In this last section, we show how other firm level characteristics respond to change in our demand variable. We directly regress our main demand variable $D_{ft}^{M_s}$ on the first difference of employment, sales and wages. We then remove the export intensity coefficient in front of $D_{ft}^{M_s}$, that is, we define

$$\tilde{D}_{ft}^{M_s} = \sum_{j,s} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst},$$

which is expected to better predict changes in exports (see Mayer et al., 2016) and test its effect on the first difference of the firm exports and of its total sales from exporting.²⁴ We add

²⁴These two values are theoretically identical but comes from two different data sources and are not always equal.

a sector×year and firm fixed effects. We then do the same exercise but replacing our dependent variables by the log of the level instead of the first differences. Results are shown in Tables 3.11 and 3.12 respectively in first difference and in log. The regression is run on two samples, first on all firms, and second on firms that were above the median in terms of export intensity at t_0 . For this latter sample, we expect the effect of the export demand to be stronger. From these tables, we see that the effect of the demand variable is positive and significant on both the variation and level of employment, sales, wages and export of all firms, but more clearly for firms that are more export intensive.²⁵

²⁵Similar tables adding an interacting terms with the productivity decile can be found in Appendix B.2 (see Tables B.10 and B.11)

Table 3.11: Other Dependent Variables - First Differences

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	0.031*** (0.008)	0.025** (0.011)	0.019** (0.009)	0.014* (0.008)	-0.004 (0.006)
Nb of observation	69,472	69,793	69,731	66,780	69,511
R ²	0.158	0.143	0.121	0.085	0.061
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	0.039*** (0.011)	0.029** (0.014)	0.026** (0.012)	0.024** (0.024)	0.022* (0.013)
Nb of observation	33,167	33,319	33,291	32,859	33,210
R ²	0.179	0.160	0.134	0.120	0.081

Notes: This table presents regression results of an OLS estimation of a regression of the first difference of various firm specific characteristics on our demand variable. $\tilde{D}_{ft}^{M_s}$ represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 3.12: Other Dependent Variables - Level

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	D_{ft}^{Ms} (1)	D_{ft}^{Ms} (2)	D_{ft}^{Ms} (3)	\tilde{D}_{ft}^{Ms} (4)	\tilde{D}_{ft}^{Ms} (5)
Demand	0.006 (0.026)	0.057** (0.029)	0.032 (0.026)	0.047*** (0.014)	0.012 (0.013)
Nb of observation	75,879	76,176	76,041	71,173	66,212
R ²	0.947	0.946	0.950	0.875	0.885
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	D_{ft}^{Ms} (1)	D_{ft}^{Ms} (2)	D_{ft}^{Ms} (3)	\tilde{D}_{ft}^{Ms} (4)	\tilde{D}_{ft}^{Ms} (5)
Demand	0.163*** (0.033)	0.258*** (0.037)	0.184*** (0.033)	0.126*** (0.028)	0.093*** (0.024)
Nb of observation	36,091	36,227	36,163	35,441	32,832
R ²	0.952	0.939	0.955	0.887	0.894

Notes: This table presents regression results of an OLS estimation of a regression of the log of the level of various firm specific characteristics on our demand variable. \tilde{D}_{ft}^{Ms} represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

3.5 Conclusion

In this chapter we analyzed the impact of export shocks on innovation for French firms. A model of trade and innovation with heterogeneous firms predicts that a positive export shock should raise innovation more for initially more productive firms. Demand shocks generate both market size and competition effects. A larger market size increases the incentives for innovation for all firms, whereas the increased competition generated by the larger market reduces the incentives for innovation most strongly for less productive firms. Our model highlights how the increased competition from higher demand can generate losses and hence lower incentives for innovation for a subset of less productive firms. We find very strong confirmation of both this market size and competition effect for French manufacturing innovators. Our empirical work merges three exhaustive firm-level datasets: customs, patent, and production data. We show that patenting responds very strongly to increases in export demand, but only for relatively more productive firm (closer to the technology frontier). This patenting response steadily increases for firms that are closer to the technology frontier (higher initial levels of productivity).

Our analysis can be extended in several directions. A first direction will be to use the same data to explore the effect of imports on innovation, using the same comprehensive databases. This would allow us to better understand why [Bloom et al. \(2016\)](#) and [Autor et al. \(2016\)](#) get opposite conclusions. A second direction would be to look at the impact of exports on the citations to previous innovations, thereby shedding new light on the knowledge spillover effects of trade. These await future research.

CHAPTER 4

Adjustment Costs and Factor Demand: New Evidence From Firms' Real Estate

4.1 Introduction

This chapter studies the effect of adjustment costs of corporate real estate on factor demand. By linking the adjustment of firms' premises to local relocations, we are able to empirically explore the impact of adjustment costs on firms' dynamics. These costs include a tax on realized capital gains, induced by the selling of the previous premises, that depend on the dynamics of local real estate prices since the acquisition date. Using a large firm-level database merged with local real estate prices, we document sizable effects of the adjustment costs on firms' labor demand and derive new results on the causes and implications of firms' local relocation.

There is a vast literature on the nature and the effect of adjustments cost on firms' factor demand.¹ This literature notably explores the effect of different structures of costs and uses firm-level data to test their empirical relevance: [Cooper and Haltiwanger \(2006\)](#) document how models that mix both convex and non-convex capital adjustment costs better fit the data. Adjustment costs are also related to a recent literature that has empirically documented the magnitude of the detrimental effect on aggregate productivity of misallocating resources toward less productive firms. Although, as noted by [Restuccia and Rogerson \(2017\)](#), the misalloca-

¹In the case of employment see [Hamermesh \(1989\)](#); [Caballero et al. \(1997\)](#); [Cooper and Willis \(2009\)](#) and [Bloom \(2009\)](#). In the case of capital see [Caballero et al. \(1995\)](#); [Cooper and Haltiwanger \(2006\)](#) and [Bloom \(2009\)](#)

tion of production factors has been chiefly traced to policy distortions (Olley and Pakes, 1996; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009 and, in the case of France, Garicano et al., 2016), adjustment costs are innately mentioned as impediments to the optimal allocation of resources. For example, Asker et al. (2014) link the dispersion of static measures of capital misallocation to the dynamic choice of production inputs. In our study, we focus on the distorting impact of adjustment costs of real estate assets because of observable heterogeneity in these costs at the firm level. The relevance of studying corporate real estate is arguably substantiated by recent findings on the role of land in the misallocation of production factor. Duranton et al. (2015) use micro data on Indian firms and find that misallocation of manufacturing output is mostly due to an inefficient allocation of land across firms.

Our empirical identification relies on the equivalence between the alteration of the premises' volume and local relocation of single establishment firms. This equivalence matters because relocation costs vary across firms and across time and because the underlying determinants of those costs are observable for both non-relocating and relocating firms. This equivalence is warranted by the argument put forward by Schmenner (1980) that on-site expansion, out-site expansion (branching) and relocation are not substitute to one another and that the latter is the only option for many firms when it comes to altering the size of the premises.² Firms' relocation is actually a fairly frequent event: with definitions that will be clarified below, we find that 1.7% of the French firms relocate their activities to a neighbouring city, on average, each year. In line with our argument on the intertwining of factors' adjustment and relocation, this yearly propensity to relocate reaches more than 4% for firms at the upper workforce growth decile.

To guide our empirical investigations, we build a general equilibrium model with heterogeneous

²On-site expansion, especially in the non-manufacturing sector and/or in urban areas, is often an option that has to be discarded because access to adjacent land or premises is constrained. Informal talks with market participants indicate that sublease of unused premises has been at a very early stage of development over the studied period. Out-site expansion is potentially associated with additional on-going costs resulting from fixed expenses per establishment and important losses of synergies. This point is further discussed in Section 4.2.

firms to derive predictions on the effect of the level of the fixed costs associated with real estate adjustment on the workforce growth across the productivity shocks distribution. In this framework, profit-maximizing firms are heterogeneous with respect to their productivity level and make decisions on labor and real estate inputs in a context of adjustable real estate inputs conditional on paying a non-convex cost. The level of these adjustment costs deter some firms from optimally adjusting their real estate inputs to the new productivity level and the complementarity between real estate and labor in the production process implies that it also affects firms' labor demand. We derive the existence of an interval of inaction for the difference in size between the optimal premises and the occupied ones in which firms prefer not to adjust their real estate inputs. Such an interval is a classical result of the literature on investment with non-convex adjustment costs (see e.g. [Grossman and Laroque, 1990](#)). In our framework, this non-relocating interval entails that firms affected by low positive productivity shocks operate in sub-optimally small premises whereas those affected by low negative productivity shocks operate in sub-optimally large premises. The complementarity between real estate and labor leads these firms to restrain employment growth as compared to the counter-factual employment growth that would be observed had those firms adjusted real estate. We show that the interval of inaction widens with the level of the adjustment costs and so do the number of firms affected. We also show that the non-relocating interval is not centered in zero and that a rise in the fixed adjustment costs has asymmetrical effects on the bounds of the interval. The effect of such a rise is larger in absolute value on the positive bound of the interval than the effect on the negative bound which implies that an increase in the fixed adjustment cost has an overall negative impact on mean firm-level employment growth. This asymmetry property strengthens with the level of the adjustment cost. As noted by [Elsby and Michaels \(2014\)](#), it is weak when the frictions is small. Nonetheless, for values that, as we shall see, are empirically relevant, it become significant.

We then test these predictions using data on single-establishment firms and their location

covering mainland France from 1994 to 2013. Our empirical study focuses on inter-municipality relocations occurring over a short distance that leave the economic environment of the firm (e.g, localized aggregate increasing return, real estate prices or wages) largely unaltered and are more likely to be primarily triggered by the inappropriateness of the site’s characteristics.³ We study the effect of adjustment costs of real estate by exploiting two types of heterogeneity in relocation costs. First, by comparing firms that own their premises and firms that rent them. Second, and in order to deal with the important unobserved differences between these two groups of firms, by restricting to real estate owners and by exploiting the latent tax on realized capital gains affecting real estate assets that owning firms must pay when they relocate.⁴ Heterogeneity in the level of this tax naturally come from the way it is designed. In a nutshell, the tax base is determined by the size of the real estate assets, the acquisition date and the dynamic of local prices since this acquisition. This scheme introduces important variability across firms and across time in the level of the relocation costs. We document that higher relocation costs lower firms’ propensity to relocate and namely constrain employment growth of the growing firms. Our baseline results suggest that a reduction of the relocation costs, through a decrease of the share of the real-estate market value that would be paid as a tax on capital gains of 1 standard deviation, would increase the propensity to relocate of affected firms by 10% and would raise the yearly employment growth rate of the growing firms by 5%. Such reduction in the adjustment costs would therefore result in an important increase in job creation and job reallocation in the most productive firms. Additional empirical evidences suggest that this reduction in the adjustment costs would foster optimal allocation of factor inputs.

Our identification strategy shares similarities with the emerging literature on the effect of tax

³Focusing on local relocations is also justified by the fact that in such cases, employees are more likely to remain in the firm; which is not the case for relocations over longer distances: [Weltevreden et al. \(2007\)](#) shows that when the relocation distance exceeds 20km, most employees quit there jobs in anticipation of the relocation decision.

⁴Indeed, for single-establishment firms holding the real estate assets in which they operate, a relocation is necessarily associated with the sale of previously occupied premises if we make the reasonable assumption that limited access to funding prevents the firms from concomitantly owning various premises.

friction on real estate transactions and households' mobility. [Dachis et al. \(2012\)](#), [Best and Kleven \(2017\)](#) and [Hilber and Lyytikäinen \(2013\)](#) all study the effect of transaction tax on residential real estate dynamic and find large aggregate effects. [Hilber and Lyytikäinen \(2013\)](#) exploit cut-off values in the tax associated with housing transactions to claim that an increase in transaction cost by 2 to 3 percentage points reduces mobility by 30%; this is only true for short distance relocations, suggesting that frictions may lead to misallocation of dwellings in the housing market. In the same vein, this chapter is also related to the literature that studies the impact of the tenure status in the residential housing market on job mobility and labor market outcomes. This literature typically finds that a high share of home-owners impairs the good functioning of the local labor market because of the real estate transaction costs associated with home-owners relocation ([Oswald, 1996](#), [Battu et al., 2008](#), [Munch et al., 2008](#)).

The chapter is organized as follows: section [4.2](#) presents stylized facts on the interaction between relocation behaviour and employment dynamics. Section [4.3](#) presents a theoretical framework development to formulate testable predictions on firms' behaviour. Section [4.4](#) presents our empirical analysis, findings and comments and section [4.5](#) concludes.

4.2 Background

Little is known about firms' local relocations and their connection to firms' employment dynamism. Most of the existing literature has rather focused on explaining the determinants of relocation and the choice of the destination. It is acknowledged that, although external factors (characteristics of potential new sites) are at play in the choice of the place of relocation, internal factors (size, age, tenure status, sector and growth) are the main predictors of firms' relocation decision (see for example [Pellenbarg et al., 2002](#) and [Brouwer et al., 2004](#)). This first section sheds light on stylized facts supporting our views that there exists a close relationship between firms' local relocation and factors' adjustment. After briefly presenting the

databases, we look at some general characteristics of firms' relocation. We then document that employment dynamics and local relocations are closely intertwined.

4.2.1 Data

To derive our results, we use a firm level database with information on a large number of French firms over the period 1994-2013 called **FiBEn**. **FiBEn** is built by the Bank of France from fiscal documents and contains detailed information on flow and stock accounting variables, notably on real estate assets, as well as information on firms' activities, location and workforce. We restrict to single-establishment firms that remain below 250 employees⁵. Below this threshold, 85.7% of the firms are single-establishment. The firm reports the code of its current municipality and we use changes in this code to detect inter-municipality relocations. This database is then merged with local residential real estate prices. We use the *Notaires*-INSEE⁶ apartment price indices built by [Fougère and Poulhes \(2012\)](#) which are based on the data collected by the French solicitor association to derive capital gains on real estate assets. Residential housing prices are used in this study because French corporate real estate prices at the local level are not available over the studied period.⁷ We describe our dataset and the variable construction in more detail in [Appendix C.1](#).

4.2.2 Firms' mobility in France

Our firm-level database allows to identify inter-municipality relocations of single-establishment firms between 1994 and 2013. We observe 124,191 single-establishment firms over an average

⁵This size restriction is made to limit measurement errors in real estate volume and location, see [Appendix C.1](#) for more details.

⁶Solicitor is the English equivalent for the French word *notaire* and INSEE is the French National Statistical Bureau.

⁷As noted by [Fougère et al. \(2017\)](#), there is evidence that, at the national level, prices in the different segments of the real estate market, and notably residential and corporate real estate, follow similar trends

period of 9.93 years. Among these firms, 22,057 have relocated their activities to another municipalities over the period of observation; that is approximately 18% of the firms. Half of the relocations concerns a relocation where the municipality of departure and the municipality of settlement are distant by less than 8km. For a little more than 70% of the relocations, this distance is inferior to 15km. These first empirical results are in line with other studies that report statistics on the distance between the place of departure and the place of settlement of relocating firms. They find that local relocations account for the large majority of the relocations (Pen and Pellenbarg, 1998; Delisle and Laine, 1998; Weltevreden et al. (2007) and Knoblen et al., 2008). In France, Delisle and Laine (1998) document that 6.2% of the firms had relocated between 1989 and 1992, with more than three quarters of the inter-municipality relocations being characterized by a distance inferior to 23km. Similarly, in Netherlands, Weltevreden et al. (2007) shows that between 1999 and 2006, most relocations are made within the same labor market area. We hereafter define as “local” a relocation that is characterized by a distance of less than 15km, between the municipality of departure and the municipality of settlement.⁸ The distribution of the relocating distance is given in Figure C.1 in Appendix C.1.

Table 4.1 presents some basic descriptive statistics to compare relocating firms to a control group made of static firms. We notice that relocating firms do not differ much by their size, their employment level and their profitability (even if some of those small differences are statistically significant). Slightly larger differences are observed for the age of the firm; static firms being in average 1.8 year older than relocating firms. Yet, sizable and statistically significant differences are observed regarding two characteristics: (i) the yearly mean employment growth over the observation period: while the mean yearly workforce growth of relocating firms is equal to 5.3%,

⁸Following this definition 73.4% of the relocations observed in our sample are local. There is of course a degree of arbitrariness in setting such a threshold. As mentioned before, it reflects the idea that relocations over farther distance are more likely to alter the local economic conditions and might require that the existing employees change their place of residence, inducing higher costs and new risks. All our subsequent results are robust to using different thresholds or to defining as local the relocations occurring within the local labor market area based on commuter flows from census data, see Appendix C.4.

it is 2.5% for static firms; (ii) the tenure status of the firm: 26% of the relocating firms report real estate holdings while this share is equal to 39% for static firms.

Table 4.1: Key summary statistics - relocating locally and static firms

	Mean		Difference	
	Relocating locally	Static		
Employment	18.9	20.1	-1.17***	(0.19)
Sales	3.14	2.98	0.16***	(0.06)
BS size	2.11	2.27	-0.16	(0.20)
Profits	0.135	0.124	0.011***	(0.0013)
Age	12.0	13.8	-1.8***	(0.11)
Employment growth	5.3%	2.5%	2.8%***	(0.0013)
Real estate owner	26%	39%	13%***	(0.004)
Observations	18,193	105,998	–	

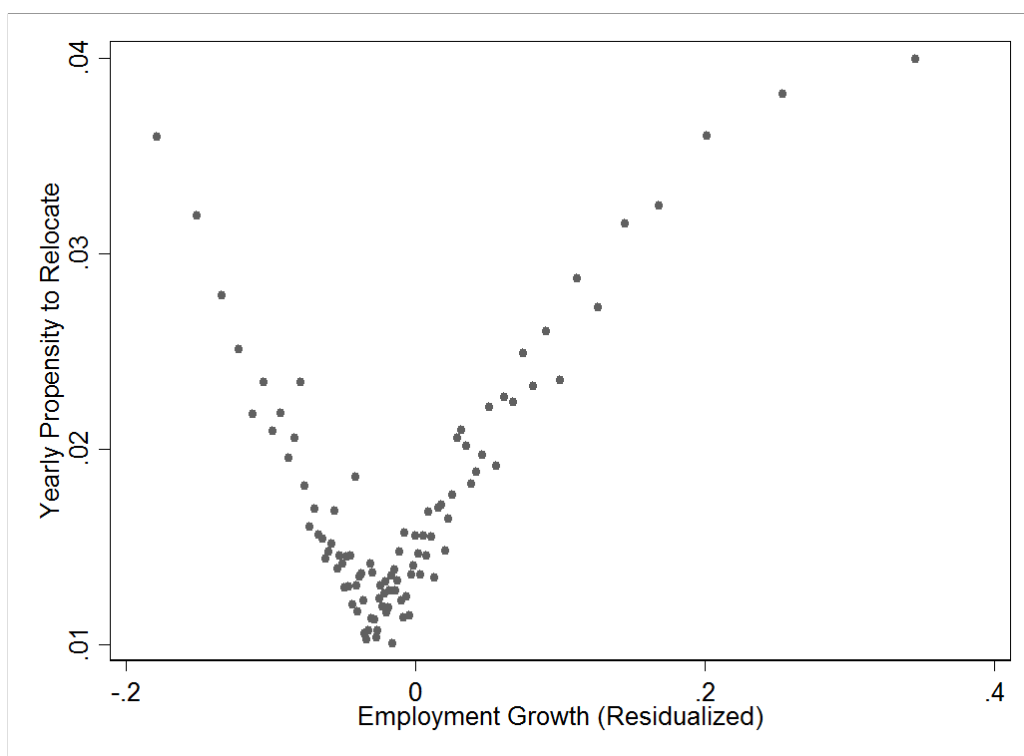
Notes: This table shows the mean of different key variables, in initial year of observation, for firms that locally relocate and for firms that neither relocate nor shift towards a multi-establishment structure over the observed period. Employment is given in full-time equivalent (FTE) number of workers as reported by the firm; Employment growth in the mean yearly percentage change in FTE over the observation period; Sales are in millions of euros; BS size is the net value of the assets reported in the balance sheet and is given in millions of euros; Profits is the Earning Before Interest and Tax margin (i.e., EBIT to Sales ratio); Age is the number of year since company's incorporation; Real estate owner is a dummy variable equal to 1 if the firm reports real estate holdings and 0 otherwise. Source: FiBEn, see Appendix C.1 for more detail about the data. The latest column show the mean and standard deviation of the difference between the two coefficients and the Student t-stat on the nullity of this difference. ***, ** and * indicate that the null hypothesis of this test is rejected at the 1%, 5% and 10% level of significance, respectively.

4.2.3 Relocating behaviour and workforce growth

The average workforce growth of relocating firms reported in table 4.1 suggests that relocation is markedly related to factors' adjustment. In order to explore this relationship, we rank firms according to their mean yearly workforce growth rate over the observation period. In each percentile of this average workforce growth distribution, we compute the propensity to relocate by dividing the number of observed local relocations by the number of observations in this percentile. The results are presented in Figure 4.1 where average employment growth has been

residualized on a complete set of sector-*département* dummies. We find that firms located in the first two deciles (*resp.* in the three last deciles) in the workforce growth distribution, which corresponds to an average yearly workforce growth rate below -4.0% (*resp.* above 1.5%), have a much higher propensity to relocate than firms characterized by limited change in their workforce size.

Fig. 4.1: Propensity to relocate and employment growth



Notes: Employment growth is taken as the average employment growth over the period of observation and residualized on a set of sector-*département* dummies. The propensity to relocate is calculated as the number of observed local relocation divided by the number of years of observations. These two variables are averaged for each percentiles of the distribution of the residualized employment growth. The first and the last percentiles have been removed to focus on the core of the distribution. Period of observation: 1994-2013. Source: FiBEa, see Appendix C.1 for more details about the data.

These results are robust to restricting to different sectors or areas. One could for example believe that service firms are more prone to relocate than manufacturing ones and are in larger quantities in major cities which are rich and dynamic areas where firms grow faster. In Appendix C.2, we report the results of a similar analysis focusing on Paris (Figure C.3(a)), Lyon (Figure

C.3(b)) and Marseilles (Figure C.3(c)) areas which are the three largest cities in France. We also present the relationship between the propensity to relocate and employment growth in the whole country but these three areas in Figure C.3(d). We can see that the U-shaped relationship is robust to such stratification and seems to be, as expected, stronger in the Paris area where on-site expansion is arguably more constrained. Finally, Figures C.2(b) and C.2(a) report the results when focusing on service industries (Figures C.2(b)) and manufacturing firms (Figures C.2(a)). The link looks stronger in the service industries, where relocating costs are arguably lower and on-site expansion is more constrained.

In the following section, we develop a theoretical framework that relies on this link between real estate adjustment and local relocations.

4.3 Model

In this section, we develop a standard model of monopolistic competition with heterogeneous firms in the spirit of Melitz (2003). Firms face a productivity shock and make the decision to adjust the size of its premises or not. Premises' size adjustment is associated with fixed relocation costs. This model sheds light upon the effect of the fixed adjustment costs of real estate on firms' behavior across the productivity distribution.

4.3.1 Model setup

4.3.1.1 Demand

There is a continuum of products $i \in [0, 1]$ and a final sector using all products i as inputs to produce Y with a CES technology:

$$Y = \left[\int_0^1 y(i)^{1-\varepsilon} di \right]^{\frac{1}{1-\varepsilon}}. \quad (4.1)$$

where ε is the inverse of the elasticity of substitution.

The conditional demand function for $y(i)$ can be written as

$$y(i) = \left[\frac{P}{p(i)} \right]^{\frac{1}{\varepsilon}} Y, \quad (4.2)$$

where P is the final good price and $p(i)$ is the price of $y(i)$. From the zero profit condition of the final good producer, we obtain:

$$P = \left[\int_0^1 p(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}}. \quad (4.3)$$

4.3.1.2 Production

Each product i is produced by a monopolistic firm indexed by i with a Cobb-Douglas production function using labor and real estate as inputs.⁹ These firms differ by their parameters $\theta(i)$ such that:

$$y(i) = \theta(i) \left(\frac{l(i)}{\alpha} \right)^\alpha \left(\frac{r(i)}{1-\alpha} \right)^{1-\alpha}. \quad (4.4)$$

θ can be understood in many different ways, it can encompass a firm-specific demand shock, technology level or the quality of the intermediate input as in [Aghion and Howitt \(1992\)](#) or managerial ability as in [Garicano et al. \(2016\)](#), in what follows we will refer to it as the firm

⁹Including productive capital stock as an input won't affect our theoretical prediction if we assume that adjustment costs in real estate are not affected by the level of capital stock. Hence, in this framework, l already encompasses the stock of capital.

productivity. Labor and real estate are mobile across firms in the intermediate sector. The endogenous market wage, w , and the endogenous market price of one unit cost of real estate, u , that can be thought as either the user cost of real estate capital or its renting rate, are the same at each firm $i \in [0, 1]$. The firm i considers the demand function and takes into account the fact that prices $p(i)$ adjust to:

$$p(i) = \frac{Y^\varepsilon P}{\theta(i)^\varepsilon} \left(\frac{l(i)}{\alpha} \right)^{-\alpha\varepsilon} \left(\frac{r(i)}{1-\alpha} \right)^{-(1-\alpha)\varepsilon}, \quad (4.5)$$

hence, firm i 's revenue is given by:

$$p(i)y(i) = \Omega(i) \left(\frac{l(i)}{\alpha} \right)^{\alpha(1-\varepsilon)} \left(\frac{r(i)}{1-\alpha} \right)^{(1-\alpha)(1-\varepsilon)}, \quad (4.6)$$

where $\Omega(i) = \theta(i)^{1-\varepsilon} Y^\varepsilon P$ is the revenue productivity (see [Foster et al. \(2008\)](#) and [Hsieh and Klenow \(2009\)](#)).

4.3.1.3 Resource constraint

We consider a closed economy where a representative consumer owns the intermediate firms, real estate assets and provide labor. Aggregate labor and real estate are in fixed-supply and we set them to L_s and R_s , respectively. In equilibrium, aggregate demand for labor and real estate equal aggregate supply.

4.3.1.4 The problem of the firm

Each firm i faces an unanticipated productivity shock on $\theta(i)$. This shock is assumed to be idiosyncratic and uncorrelated with the observable characteristics of the firm. After observing its new level of productivity $\theta(i)$, the firm adjusts labor and can adjust real estate conditional

on relocating. This condition relies upon the constrained on-site expansion and the constrained sublease of vacated premises hypotheses. We denote $z(i)$ the decision variable with $z(i) = 1$ if firm i relocates and $z(i) = 0$ otherwise. Relocating is associated with costs that we will specify below in order to relate them to actual costs faced by relocating firms. In this theoretical framework, we model these costs as proportional to the size of the endowed premises. This specification aims at capturing the fact the fixed costs vary with the size of the premises and at simplifying mathematical expressions. Formally, the costs are equal to $ar_0(i)$, where $r_0(i)$ is firm i 's initial premises volume and a is a non-negative real number.¹⁰

Because of the fixed adjustment costs, a firm may decide to remain in its latest premises even it is hit by a non-zero productivity shock (see [Cooper et al., 1999](#) and [Cooper and Haltiwanger, 2006](#) for a thorough discussion on the implication of non-convex adjustment costs on investment decision).

The price of both inputs are taken as given by the profit maximizing firms. Finally, firm i 's decision problem can be written:

$$\max_{z(i) \in \{0,1\}} \left[z(i) \max_{\substack{r(i) > 0; l(i) > 0 \\ p(i) > 0}} [\pi(i, r(i)) - ar_0(i)] + (1 - z(i)) \max_{\substack{l(i) > 0 \\ p(i) > 0}} [\pi(i, r_0(i))] \right], \quad (4.7)$$

where $\pi(i, r(i))$ denotes the profit function of firm i defined as $p(i)y(i) - wl(i) - ur(i)$. In what follows, we shall call $\pi^{(1)}(i)$ the optimal profit in the case of a relocation and $\pi^{(0)}(i)$ in the case of no relocation.

¹⁰Notice also that the predictions of the model are unaltered if we introduce linear or/and convex adjustment costs in addition to those fixed costs. We focus on the consequences of changes in the value of parameter a , that is to say of the parameter governing the level of the fixed costs, because we observed firm level variation with respect to a fixed costs in the data.

4.3.2 Solving the model

4.3.2.1 Decentralized equilibrium

The equilibrium is defined by a vector of allocation $\{r(i), l(i), y(i), z(i), Y\}$ and a vector of prices $\{P, p(i), u, w\}$ such that:

- Given $\theta(i)$, u and w , $\{r(i), l(i), z(i), p(i)\}$ maximize firm i 's profit for every i as defined in equation (4.7) (and $r(i) = r_0(i)$ if $z(i) = 0$).
- Final good producing competitive firm chooses $y(i)$ for all i to produce Y by maximizing its profit taking $p(i)$ as given.
- Labor and real-estate market clear.

4.3.2.2 The friction-less case

In the simple case where $a = 0$, we show in Appendix C.3.1 that our model yields the following optimal allocation:

$$z(i) = 1 ; l(i) = \frac{\theta(i)^{\frac{1-\varepsilon}{\varepsilon}}}{\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di} L_s \text{ and } r(i) = \frac{\theta(i)^{\frac{1-\varepsilon}{\varepsilon}}}{\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di} R_s \quad \forall i \in [0, 1] \quad (4.8)$$

Normalizing P to 1, we show that prices are endogenously set as follows:

$$u = (1 - \varepsilon) \frac{1 - \alpha}{R_s} Y ; w = (1 - \varepsilon) \frac{\alpha}{L_s} Y \text{ and } p(i) = \frac{1}{\theta(i)} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{\varepsilon}{1-\varepsilon}} \quad (4.9)$$

and that aggregate production is equal to:

$$Y = \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{\varepsilon}{1-\varepsilon}} \left(\frac{L_s}{\alpha} \right)^\alpha \left(\frac{R_s}{1 - \alpha} \right)^{1-\alpha}. \quad (4.10)$$

In particular, without friction, this model generates an optimal factor allocation in the sense that the allocation maximizes Y and is uniquely determined by the firm's productivity.

4.3.2.3 The case with frictions

To find the equilibrium allocation following productivity shocks in the case with frictions on real estate adjustment, we need to make an assumption on the distribution of $r_0(i)$. We hence consider that, before the productivity shock, the allocation of production factors corresponds to the one derived in the friction-less case. This implies that $r_0(i)$ only depends on $\theta_0(i)$, the initial level of productivity. In our baseline experiments, to simplify the interpretation of the results, we consider that the productivity distribution is left unaltered by the productivity shocks. Firms merely redraw their productivity level from a stationary productivity distribution.¹¹ Doing so, we abstract from the general equilibrium effect resulting from aggregate productivity shocks and we focus on the general equilibrium effects attributable to changes in the allocation of resources entailed by the adjustment costs. Labor adjustment being friction-less, $l(i)$ always satisfies the first order conditions. Conversely, $r(i)$ only satisfies first-order conditions if $z(i) = 1$, otherwise $r(i) = r_0(i)$. If $z(i) = 1$, it is easy to show that firm i 's profit, denoted $\pi^{(1)}(i)$, is:

$$\pi^{(1)}(i) = \frac{u\varepsilon}{(1-\alpha)(1-\varepsilon)} r^*(i) - ar_0(i), \quad (4.11)$$

where $r^*(i)$ denotes the optimal volume of real estate conditional on $z(i) = 1$.

Whereas if $z(i) = 0$:

$$\pi^{(0)}(i) = \frac{u(1-\alpha(1-\varepsilon))}{(1-\alpha)(1-\varepsilon)} r^*(i)^{\frac{\varepsilon}{1-\alpha(1-\varepsilon)}} r_0(i)^{\frac{(1-\alpha)(1-\varepsilon)}{1-\alpha(1-\varepsilon)}} - ur_0(i). \quad (4.12)$$

¹¹In the following subsection, presenting results from numerical simulations, we explore the behaviour of the model when the economy faces an aggregate productivity shock in addition to idiosyncratic shocks.

The relocation condition, $\pi^{(1)}(i) > \pi^{(0)}(i)$, can be written as a simple condition on $\Delta_r(i) = \frac{r^*(i)}{r_0(i)} - 1$, the percentage change in size between the optimal premises following the shock and the endowed premises:

$$\frac{u}{(1-\alpha)(1-\varepsilon)} \left(\varepsilon(1 + \Delta_r(i)) - (1 - \alpha(1 - \varepsilon)) (1 + \Delta_r(i))^{\frac{\varepsilon}{1-\alpha(1-\varepsilon)}} \right) + u - a > 0. \quad (4.13)$$

Because endowed premises' size $r_0(i)$ is proportional to $\theta_0(i)^{\frac{1-\varepsilon}{\varepsilon}}$ and optimal premises' size $r^*(i)$ is proportional to $\theta(i)^{\frac{1-\varepsilon}{\varepsilon}}$, there exist a direct relation between $\Delta_r(i)$ and the percentage change in productivity $\Delta_\theta(i)$. Formally, $1 + \Delta_r(i) = \lambda(1 + \Delta_\theta(i))^{\frac{1-\varepsilon}{\varepsilon}}$ where λ only depends on aggregate quantities.¹²

We show in Appendix C.3.2 that, as long as $a < u$, there exist threshold values $\Delta_r^- < 0$ and $\Delta_r^+ > 0$ such that if $\Delta_r(i)$ is included in $[\Delta_r^-; \Delta_r^+]$ it is optimal for firm i not to relocate. We label this interval the “non-relocating interval”. We show that the width of this non-relocating interval is increasing with the fixed costs. The existence of such an interval of inaction is a classical result of the literature on lumpy and intermittent adjustments resulting from fixed lump-sum cost per adjustment decision (the (S,s) rules). This literature typically finds a range of inaction defined by two outer adjustment points between which the agent allows a state variable to diverge from its optimal value.¹³

The intuition for the existence of such an interval in our framework is straightforward. When a firm receives a positive shock, its profits can be optimized by using a larger amount of inputs. Because altering the level of inputs requires to pay a fixed cost, the positive productivity shock has to be large enough so that the difference between the profits when factors optimally

¹²We indeed have $\lambda = (1 - \alpha) \int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di Y P^{\frac{1}{\varepsilon}} (1 - \varepsilon)^{\frac{1}{\varepsilon}} \frac{1}{R_s u^{\frac{1}{\varepsilon}}} \left(\frac{w}{u} \right)^{\frac{-\alpha}{1-\alpha(1-\varepsilon)}}$

¹³See Bertola and Caballero (1990) for a survey on discontinuous adjustment control policy and Grossman and Laroque (1990)'s model of consumer durable purchase for a example of such a range of inaction. Perhaps more closely related to our result, Gobillon and Le Blanc (2004) study residential mobility and find that the difference in terms of utility between the relocating household and the non-relocating household linearly depends on the square value of the difference between optimal housing stock and the previously occupied housing stock.

adjust and when factors' adjustment is constrained covers these fixed costs. Similarly, when the firm receives a negative productivity shock, its profits can be improved by trimming down the amount of inputs. Reducing the amount of input is also associated with a fixed cost that is worth to be paid only if the profits saved by optimally adjusting the production factor are substantial enough. That is to say, if the negative shock is important enough.

4.3.3 Results from simulations

To study general equilibrium effects in a model with non-zero adjustment costs, we run simulations of the model. We draw $N=100,000$ productivity levels from a normal distribution with mean μ and variance σ^2 and build the friction-less factors' endowment resulting from those draws. We then shock our economy by redrawing new productivity levels from the same distribution in order to study how factors subsequently adjust. Our function objective is to find values for Y , w and u built from the individual decisions of the 100,000 firms and satisfying all market clearing conditions. Based on this numerical resolution of the model, we explore the effect of the frictions on individual firms' behaviour and aggregate outcomes. Parameters value can be found in Table 4.2. The value of the intermediate output elasticity to real estate, $1 - \alpha$, is derived from the average ratio of the market value of structures and land over the aggregate value added of Non-Financial Corporations since 1979, based French aggregate series produced by the INSEE. The calibration of the parameter ϵ is taken from the literature that usually finds a value around 0.2 or 0.25 (Redding and Weinstein, 2016; Hottman et al., 2016). The results presented below are derived with a parameter value of 0.2.¹⁴ We study the behaviour of the model for values of a ranging between 0 and 0.1. When a is equal 0.1, the relocation costs correspond to, in average, 0.5% of the value-added.¹⁵

¹⁴The results are qualitatively unchanged when we consider $\epsilon = 0.25$. In accordance with the results analytically derived above, the asymmetrical effect of the adjustment costs is lowered for such a value of ϵ .

¹⁵This corresponds to the 95th percentile in the distribution of the tax on real estate capital gains (extensively described in the following section) over value added in our firm level database

Table 4.2: Value of parameters used in the simulation procedure.

N	μ	σ	ϵ	α
100,000	1	0.1	0.2	0.925

4.3.3.1 Adjustment costs and firm level behaviour

In the model with frictions, the non-relocating interval generates discontinuities at the bounds of the interval in the reaction of firms' labor demand to productivity shocks. Those discontinuities directly result from the complementarity between real estate and labor in the production function that conditioned optimal labor demand to the amount of real estate input. Crossing the thresholds for productivity shocks that trigger relocation has a direct impact on the firm's employment dynamics.

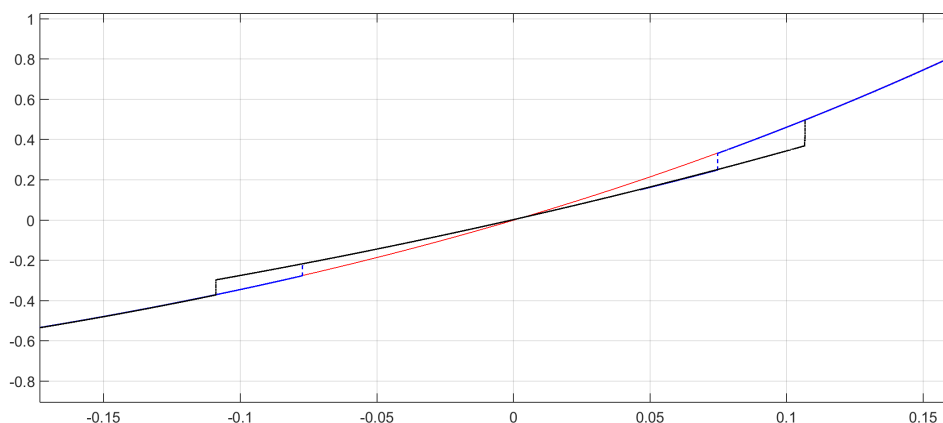
We illustrate this effect by simulating the firms' labor demand, across the whole distribution of θ , for varying levels of friction a . Those experiments are presented in Figure 4.2.

Absent any adjustment costs (red plain line ; $a = 0$), because real estate and employment jointly adjust for any productivity shocks, employment smoothly varies with changes in productivity and no discontinuity is observed as described in the friction-less model. When introducing adjustment costs, two regimes appear. Outside of the non-relocating interval, firms jointly adjust real estate and employment leading to similar dynamics as in the friction-less case.¹⁶ Within the non-relocating interval, employment adjusts to productivity shocks more sluggishly because of the predetermined level of real estate. Comparing the dynamics associated with two levels of fixed-costs (blue dotted lines ; $a = 0.05$, black dashed line $a = 0.1$), we observe that, as already noticed, the non-relocating interval widens with a .

Predictions: (i) relocating firms are characterized by larger employment growth; (ii) because of the asymmetrical effect of the adjustment costs, the growth differential is larger when the

¹⁶The differences observed between the various curves outside the intervals of inaction result from changes in input prices that are discussed below

Fig. 4.2: Employment growth as a function of productivity shocks for different values of a



firms are growing.

4.3.3.2 Adjustment costs and aggregate relocating behaviour

We have analytically derived that the non-relocating interval widens with the level of the adjustment costs. We numerically solve the model for varying parameter values of a while keeping the productivity distribution constant. We report in Figure 4.3 the share of relocating firms as function of the parameter value a . Because of the increasing width of the non-relocating interval, we observe that this share strictly decreases as a increases.

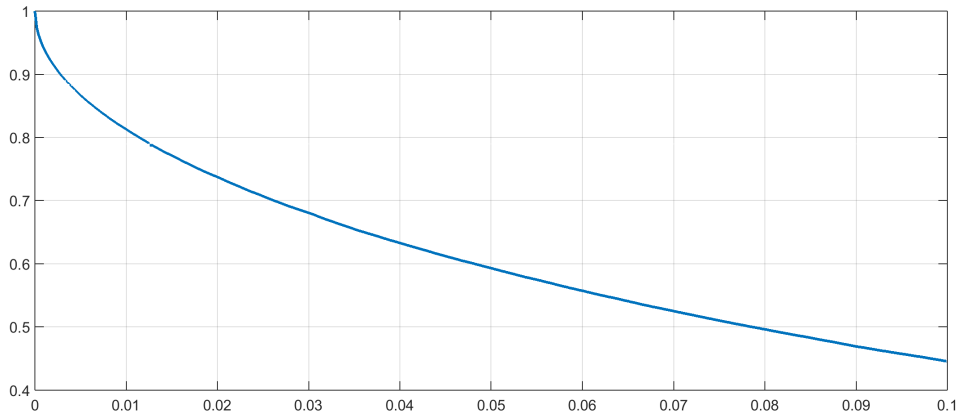
Prediction: for a given productivity distribution, the share of relocating firm is decreasing with the level of the adjustment costs.

4.3.3.3 Adjustment costs and workforce growth distribution

Ultimately, we are interested in deriving the effect of the adjustment costs on moments of the workforce growth distribution.

As the fixed costs associated with real estate adjustment rise, for a given distribution of the

Fig. 4.3: Share of relocating firms

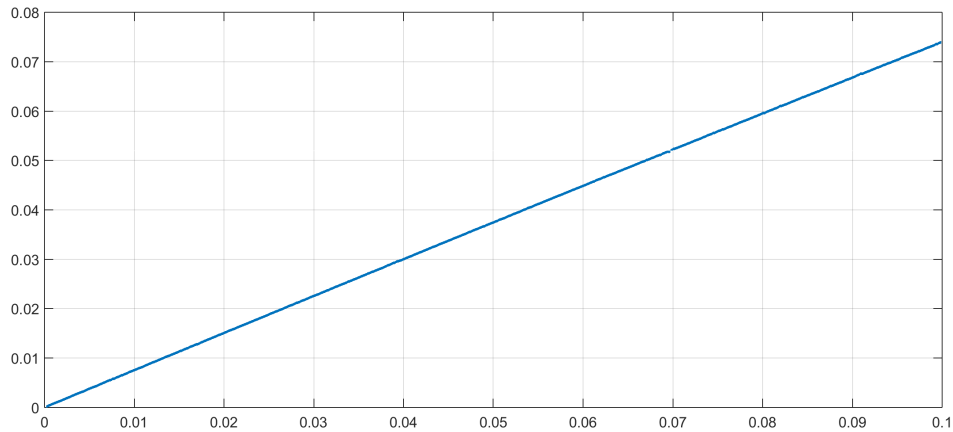


Notes: This figure plots the share of firms that optimally choose to relocate for different values of a

productivity shocks, a higher share of firms are located in the non-relocating interval. Within this interval, firms affected by positive shocks are stuck in under-sized premises that constrain employment growth whereas firms affected by negative shocks operate in over-sized premises that slow down job destruction. When studying how frictions affect the mean employment growth, we are capturing those two opposite effects.

Our simulations show that those two effects do not cancel out and that the negative effect of the frictions on the growing firms dominates. We indeed find that the mean employment growth decreases with the level of the adjustment costs (upper left panel of Figure 4.5). This is a direct consequence of the result stating that the asymmetrical effect of the adjustment costs on relocation grows with the level of the frictions. In other words, when a rises, more growing firms than declining firms enter the non-relocating interval. This can be illustrated by plotting the difference between the smallest positive percentage change in real estate size that triggers relocation and the absolute value of the largest negative percentage change that triggers relocation, for different levels of friction. We notice that when a equals 0.1, the difference between the smallest positive and the largest negative change in real estate size triggering relocation is more than 7 percentage points.

Fig. 4.4: Length of the non-relocating interval



Notes: This figure plots the difference between the smallest positive percentage change in real estate size that triggers relocation and the absolute value of the largest negative percentage change that triggers relocation for different values of a

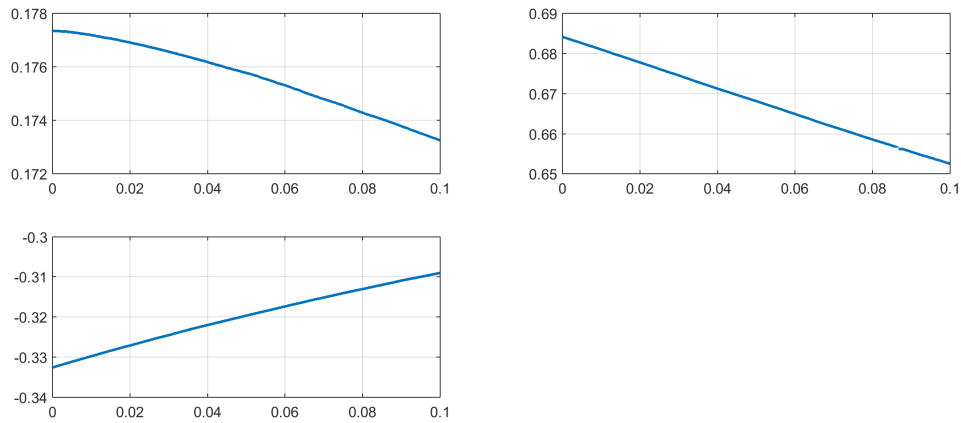
The differentiated effect of adjustment costs on employment growth depending on the sign of the productivity shock can be highlighted by studying positive and negative productivity shocks separately. We plot the mean employment growth as a function of a , conditional on positive and negative productivity shocks in the upper right panel and lower left panel of Figures 4.5, respectively. The mean employment growth of firms affected by a positive productivity shocks is sharply decreasing with a whereas a has a less marked positive impact on the employment decrease of firms stricken by negative productivity shocks.

Prediction: (i) overall average employment growth decreases with the level of adjustment costs; (ii) mean employment growth of growing firms markedly decrease with the level of adjustment costs whereas mean employment growth of declining firms slightly increases

4.3.3.4 Aggregate effects of the frictions

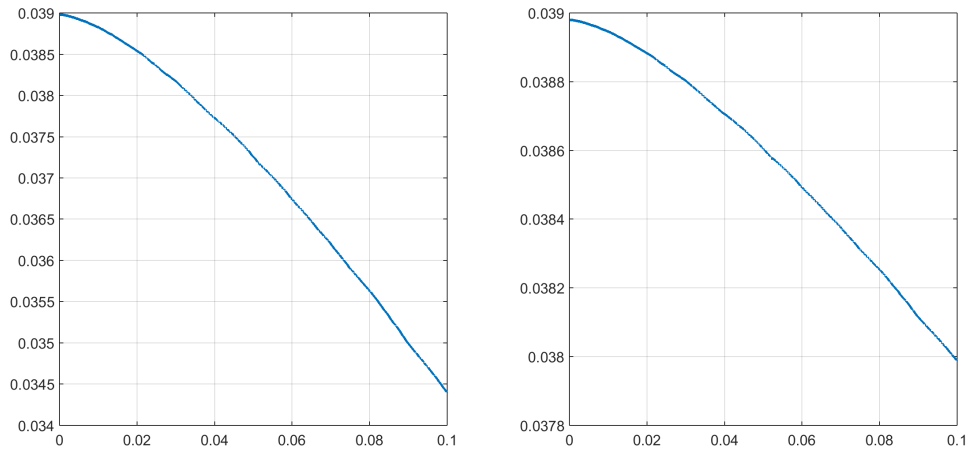
The adjustment costs hinder the optimal allocation of inputs. This results clearly appears when we observe the change in the covariance between inputs' allocation and firm level productivity as the level of the adjustment costs rise (Figure 4.6). We notice a very sharp decline in the

Fig. 4.5: Mean employment growth as a function of a



covariance between $r(i)$ and $\theta(i)$ (left panel). We observe a similar pattern for the fall of the covariance between $l(i)$ and $\theta(i)$ but the magnitude of the fall is much less pronounced (right panel) because, even if firms are constrained by their premises' size, they are still able to adjust labor following the productivity shock.

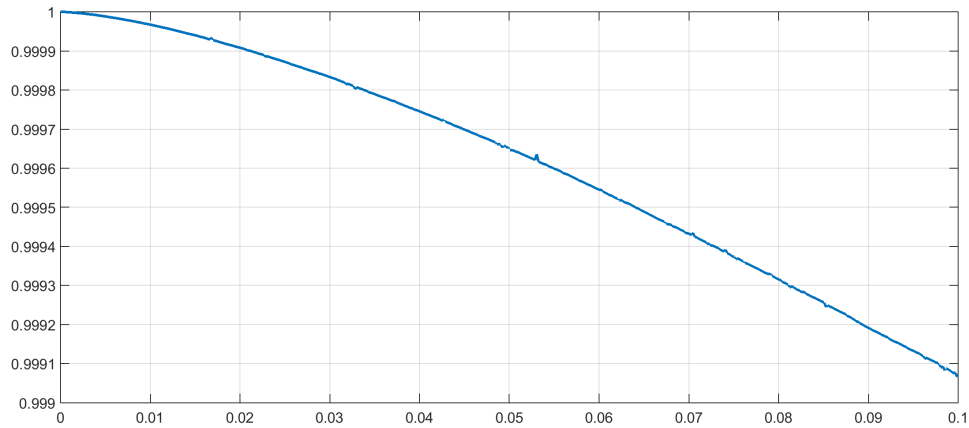
Fig. 4.6: Covariance between real-estate volume and relocation cost



Notes: This figure plots the covariance between $r(i)$ and $\theta(i)$ as a function of a

The allocation of labor across firms primarily governs the dynamics of output. In this model where aggregate supplies of corporate real estate and labor are fixed, the effect of the frictions

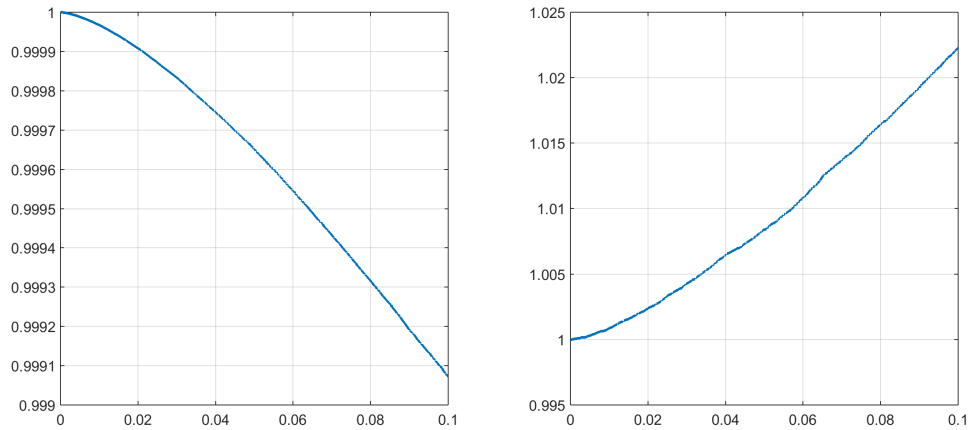
Fig. 4.7: Aggregate output as a function of a



Notes: This figure plots the the value of Y as a function of a . Standardized at 1 for $a = 0$.

on aggregate output is exclusively channeled by the allocation of inputs across firms. Because the allocation of labor is only mildly impaired by the frictions, we obtained negative, but small, negative effect of the friction on the aggregate output (Figure 4.7).

Fig. 4.8: Inputs' price as a function of a



Notes: This figure plots the equilibrium value of p as a function of a . Standardized at 1 for $a = 0$.

Our general equilibrium model sets input prices so that the real estate and the labor markets both clear. Figures 4.8 present the dynamics of the equilibrium inputs' prices when a rises.

While the negative impact of the adjustment costs on the weighted average productivity of labor puts downward pressures of the wages (left panel),¹⁷ the distortion induced by the real estate adjustment costs increases the equilibrium price of real estate (right panel). The reason for this result is the following. A rise in a implies that more firms are locked in their premises. It turns out that the supply cut induced by this additional non-relocating firms is larger than the counter-factual optimal real estate size that would be used by those non-relocating firms. As a result, a rise in a has a larger negative impact on aggregate supply than on aggregate demand and causes a sharp increase in u .

These results are derived in a framework where shocks are idiosyncratic and centered in 0. It is relevant to study the behaviour of the model in presence of an aggregate productivity shock. It can be done by shifting the productivity distribution in period 1. We present in appendix C.3.3 the figures that synthesize the simulation results obtained when the mean of the normal distribution from which individual productivity levels are redrawn in period 1 is shifted by +5%. We observe that the interval of inaction for the productivity shocks shifts to the right as a direct consequence of the general equilibrium effects affecting factor prices. Nevertheless, all the predictions that we have derived are robust to this aggregate productivity shock.

4.4 Empirical evidence

In this section, we use the firm-level dataset described in section 4.2 to test the predictions of the model. In particular, we show that firms that relocate experience a higher growth rate in their workforce (in absolute value) and that relocations and workforce adjustments are contemporaneous. We find evidence of an asymmetric impact of relocation on the number of employees between growing and declining firms. We show that relocation costs and notably the latent capital gains is negatively correlated with the occurrence of a premises adjustments. We

¹⁷In their model, [Garicano et al. \(2016\)](#) also find a negative effect of the regulation on wage.

then explore the direct effect of those adjustment costs on the workforce growth distribution.

4.4.1 Effect of a local relocation on employment dynamics

Our first set of regressions aims at confirming the predictions of our model regarding the interaction between relocation and employment growth:

1. Among growing (resp. declining) firms, the ones that relocate are characterized by higher (resp. lower) employment growth rates than the ones that do not.
2. Employment growth gap between relocating and non-relocating firms should be larger for growing firms than for declining firms, resulting in an overall positive effect of relocation on employment.

Cross-Section results

For a firm i , in sector s and *département* d , we denote Δl_i the average growth of employment over the period of observation and we first consider the following model:

$$\Delta l_i = \beta_1 z_i + \beta_2 X_i + \varepsilon_{i,s,d}, \quad (4.14)$$

where z_i is the yearly frequency of (local) relocation (the number of relocations over the number of years of observation) and X_i is a vector of firm specific characteristics taken at the initial year of observation (age, size...). $\varepsilon_{i,s,t}$ includes fixed effects at the sector times *département* level (s, d) plus an idiosyncratic error. We allow for correlation of this error terms each group of *département* and sector.¹⁸

¹⁸In our baseline specification, recall that we consider a relocation to be local if its distance is over 15km. Tables C.4, C.5, C.6 and C.7 show what happens if we change this definition.

Table 4.3: Relocation and employment dynamics - Cross section results

Dependent variable: Yearly average employment growth (in %)			
	All (1)	Growing (2)	Declining (3)
Relocate	0.125*** (0.012)	0.209*** (0.021)	-0.063*** (0.005)
Age	-0.078*** (0.004)	-0.116*** (0.008)	0.020*** (0.001)
Size	-4.078* (2.095)	-8.476*** (3.102)	4.334*** (1.608)
R ²	0.059	0.110	0.158
Observations	118,980	56,983	46,605

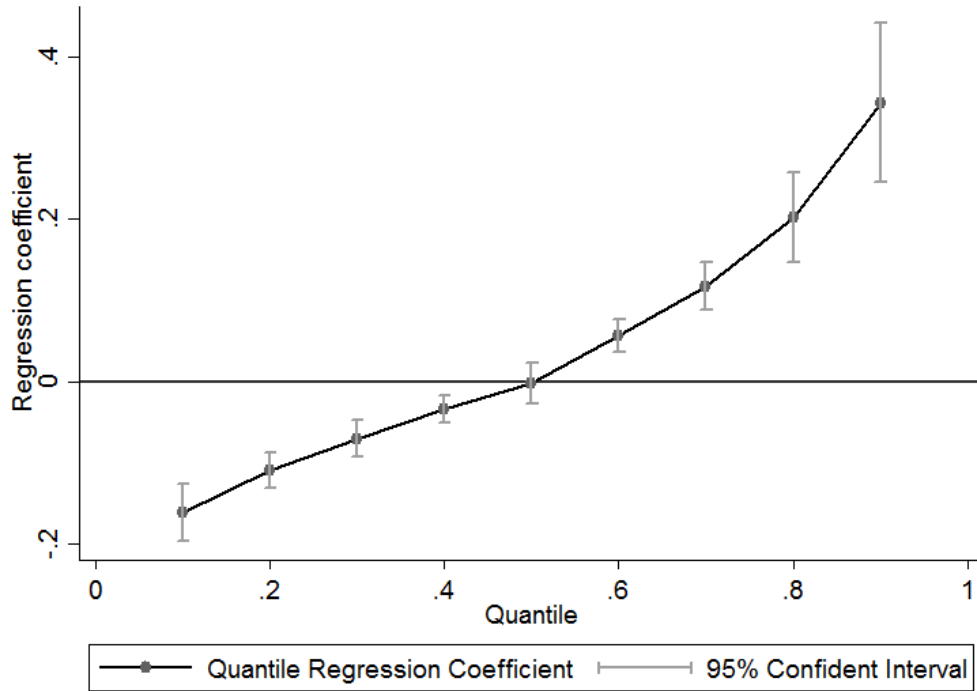
Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. Column 1 uses all firms, column 2 (resp. 3) restricts to firms with positive (resp. negative) employment growth. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Regressions include a *département* \times *sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département* \times *sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Coefficients of equation (4.14) are estimated using ordinary least square on different samples: first for all firms, then for firms with a positive average employment growth rate and finally for firms with a negative average employment growth rate. Results are respectively presented in columns 1, 2 and 3 of Table 4.3. Overall, the occurrence of a local relocation is positively associated with employment growth (column 1). The effect is positive for growing firms and negative for declining firms. For the former, results suggest that an increase in the frequency of relocation of 1 percentage point is associated with an increase in employment growth of 0.13 percentage point. Consistently with the model, relocating seems to allow firms to adjust its workforce either upward or downward. However, as suggested by the positive coefficient in column 1, the overall effect on employment growth is positive. Our results are robust to a number of robustness tests, such as considering smaller time periods to give more relevance

to initial conditions or to considering alternative definition of a local relocation. All these additional results can be found in Appendix C.4.1.

Next, to gain further insight on the heterogeneous effect of a relocation across the distribution of employment growth, we estimate equation (4.14) using quantile regression model focusing on each of the different deciles. We plot the coefficient on variable z_i along with confident intervals in Figure 4.9. Results confirm those of Table 4.3, namely that relocating is associated with a different effect depending on the firm’s position in the distribution of average employment growth. This effect changes sign around the 40th percentile, which corresponds to an average employment growth of 0.

Fig. 4.9: Relocation and employment dynamics - Quantile regression results



Notes: This graph plots the coefficients on the observed frequency of local relocation during the observed period from a cross-section quantile regression with employment growth as a dependent variable (equation (4.14)) residualized on a *département*-sector fixed effect. We plot the coefficient obtained for each of the quantile: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 along with the 95% confidence interval. Regression also includes our usual control variables: Age and Size (both taken in the first year of observation). Confidence intervals at the 95% level have been estimated with a variance-covariance matrix built with 40 bootstrap replications.

Potential concerns

One may worry that our regression capture agglomeration effects. As documented by [Delgado et al. \(2014\)](#) and [Combes et al. \(2012\)](#), regional clusters can result in an increasing growth rate of nearby firms that benefit from spillover, even if competition is stiffer. Firms are likely to be attracted by such clusters and subsequent employment growth may be affected by the new site. However, comparing the characteristics between the municipality of departure and the municipality of settlement for growing relocating firms and declining relocating firms does not show support for this alternative mechanism, as far as local relocations are concerned. Indeed, agglomeration effect would predict that growing firms relocate to larger or denser cities, or to cities where the industry in which they operate is more represented while declining firms would act conversely. Yet, in the data, we observe that both growing and declining firms tend to relocate to smaller and less dense municipalities where the level of concentration in the industry as well as its overall size are larger (see Table C.10 in Appendix C.4). This rather corroborates the results on the urban sprawling, documented in the Paris area by [Delisle and Laine \(1998\)](#).¹⁹ We do not observe any significant asymmetrical behaviour between growing and declining firms in that respect.²⁰

¹⁹This results could also be related to the idea that firms switch to mass production and relocate to specialized cities where production costs are lower as put forward by [Duranton and Puga \(2001\)](#)

²⁰Of course, other external factors may explain both a higher propensity to relocate and employment dynamics. For example, the displacement effect of publicly funded place-based programs documented by [Givord et al. \(2013\)](#); [Mayer et al. \(2015\)](#) and [Overman and Einio \(2012\)](#) can offer a potential alternative story to explain our results. A famous example in France, documented by [Mayer et al. \(2015\)](#) is the case of *Zone France Urbaine* (ZFU). Our results are however only marginally altered when we remove all firms located less than 15km away from a ZFU (see Table C.11 in Appendix C.4). There exist other differences in the level of local taxes that can also alter location choices ([Devereux and Griffith, 2003](#); [Rathelot and Sillard, 2008](#) and [Duranton et al., 2011](#)). Unfortunately, we do not have access to precise information on the local indirect taxes at the level of the municipality over the observation period that would allow us to take them into account.

Panel Fixed-Effect

Next, we take advantage of the time dimension of our sample to control for unobserved firm characteristics using fixed-effects panel regressions. We consider the following model:

$$\Delta l_{i,t} = \gamma_{1,k} z_{i,t-k} + X_{i,t} \gamma_2 + \epsilon_{i,t,s}, \quad (4.15)$$

where this time, $\Delta l_{i,t}$ denotes employment growth between $t - 1$ and t , $z_{i,t}$ a binary variable for having locally relocated between $t - 1$ and t and where control variables vector X is taken at t . $\epsilon_{i,t,s,d}$ includes fixed effects at the sector times year level (s, t) a firm fixed effect and an idiosyncratic error. We allow for correlation of this error terms within firm.

Estimation results of equation (4.15) for $k = 0$, $k = 1$ and $k = 2$ can be found in Table 4.4. The sample used in columns 1 and 3 is the same as in column 2 of Table 4.3 whereas the sample used in columns 2 and 4 is the same as in column 3 of Table 4.3. From these regressions, we see that firms experience a statistically significant modification in the size of their workforce contemporaneously with their relocation. When looking at other lags, the effect of a relocation is not significant for declining firms and only significant for $k = 1$ for growing firms.

4.4.2 Effects of adjustment costs on employment dynamics

Owners and Renters

Our second step is to identify the effect of real estate adjustment costs on employment growth. We need to find an observable measure of relocation costs that is heterogeneous across firms. One first natural candidate is the tenure status (whether the firm owns or rents its premises). Relocating is indeed less costly for renting firms than for real estate owning firms. For example, owners pay legal fees associated with real estate transactions and taxes triggered by the sales

Table 4.4: Relocation and employment dynamics - Panel Fixed-Effect results

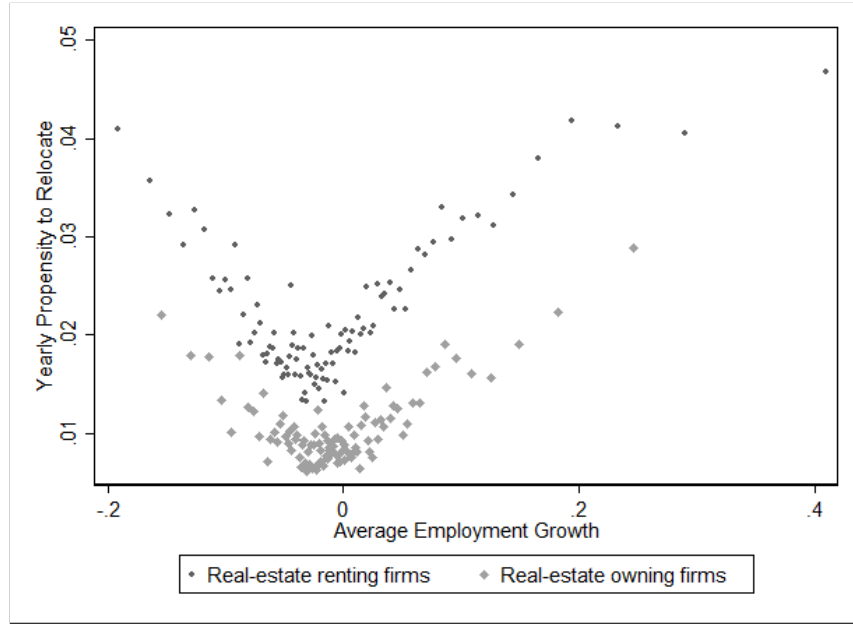
Dependent variable: Employment growth at t (in %)						
	Growing (1)	Declining (2)	Growing (3)	Declining (4)	Growing (5)	Declining (6)
Relocate $_t$	3.663*** (0.674)	-1.706*** (0.369)				
Relocate $_{t-1}$			4.079*** (0.694)	-0.085 (0.328)		
Relocate $_{t-2}$					0.805 (0.606)	0.288 (0.319)
Age	-0.259* (0.145)	-0.199 (0.150)	-0.256* (0.145)	-0.197 (0.150)	0.062 (0.146)	-0.118 (0.159)
Size	-75.674*** (23.791)	-18.514** (8.272)	-75.754*** (23.852)	-18.475** (8.266)	-69.808*** (23.326)	-27.582** (11.486)
R ²	0.149	0.100	0.149	0.100	0.167	0.138
Observations	574,352	426,728	574,352	426,728	516,131	379,077

Notes: Variables definitions are given in Table C.3. Columns 1, 3 and 5 (resp. 2, 4 and 6) restrict to firms with positive (resp. negative) average employment growth over the period 1994-2013. Relocate $_t$ is a binary variable equal to 1 if the firm has locally relocated (with a distance below 15km) between year $t - 1$ and year t . The regressions include a firm fixed effect and a sector times year fixed effect. Panel fixed effect OLS regression with robust standard errors clustered at the firm level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

of their previous real estate assets. Besides, searching costs are likely to be higher for this type of firms. We therefore expect different relocation behaviour between real estate owner firms and renting firms. This intuition is confirmed by Figure 4.10 where we replicate Figure 4.1 but separating for owners and renters. It clearly appears that not only renting firms relocate on average more than others, they also exhibit smaller changes in their workforce for a given propensity to relocate as compared to owners.

However, the choice of the tenure status is not exogenous and is likely to depend on unobservable growth prospects. One can for example imagine that a firm expecting significant increases in its workforce would prefer to rent its premises in order to be more flexible. This would cause a

Fig. 4.10: Propensity to relocate and employment growth: owners vs renters



Notes: See Figure 4.1. Owners and renters have been selected on the first year they appear in the dataset based on their reported volume of real estate. Period of observation: 1994-2013. Source: FiBEu, see Appendix C.1 for more details about the data.

reverse causality issue preventing us from associating a difference in the relocating behaviour or the employment dynamics to higher relocation costs. In fact, we show in Table C.12 of Appendix C.4 that the group of renting firms and owning firms are different in many aspects. For this reason, we turn to another measure of the relocation costs: the tax on capital gains that the firm would have to pay upon relocating.

The tax on capital gain

The tax on capital gains is a tax on the difference between the purchase and selling price of an asset. This tax is only paid by real estate owning firms when they sell their premises. However, we can always proxy its latent level at a yearly frequency at the using local real estate price dynamics. Based on balance sheet data, we recover the market value of real estate holdings by applying the accrued change in the local real estate prices since the acquisition date (approximated thanks to the ratio of the accumulated amortizations of buildings over

the gross book value of buildings) to the historical value of building. The latent capital gains correspond to the market value minus the the historical value. The tax scheme takes into account the holding period and allows to diminish the amount of capital gains by 10% each year after a five-year holding period (see appendix C.1 for more detail). The latent tax C is obtained by multiplying the marginal corporate income tax τ , which has been equal to 33% in France over the studied period, and the tax base, determined by the interaction between the acquisition date, the local dynamics of real estate prices since this acquisition and the volume of the premises. Formally:

$$C_{i,t} = \tau \left[p_t^d (1 - A(T_{i,t})) - p_{t-T_{i,t}}^d \right] r_{t-T_{i,t}} \max [0, (1 - 0.1 \max(T_{i,t} - T_0))], \quad (4.16)$$

where p_t^d is the local observed real-estate price level (taken at the *département* level), $T_{i,t}$ is the difference between year t and the date of acquisition of real-estate, $r_{t-T_{i,t}}$ is the volume of the premises at the date of acquisition and τ , T_0 are two parameters equal to 33% and 5 years respectively.

For the sake of comparability across firms, we normalize the amount of the latent tax by dividing it by the market value of real estate assets in order to obtain the share of the proceeds from the sale that would be paid under the heading of “tax on capital gains” in the event of the sale of real estate assets. The firm level variation for this quantity is driven by the interaction of the timing of the acquisition of the premises and the local price dynamism since this acquisition, the latter being mostly driven by household and larger firms that we are not considering in our analysis. In addition, because the latent tax level varies with the interaction of these two factors, the impact of each of these factors considered individually can be controlled for in our analysis. The variable that we shall denote $Tax_{i,t}$ can theoretically takes values between 0 and the marginal corporate income tax τ .²¹ We observe large variation across firms, with a little

²¹Note that $Tax_{i,t} = \frac{C_{i,t}}{p_t^d(1-A(T_{i,t}))r(t-T_{i,t})} = \tau \left(1 - \frac{p_{t-T_{i,t}}^d}{p_t^d(1-A(T_{i,t}))} \right) \max [0, (1 - 0.1 \max(T_{i,t} - T_0))]$ does not

less than half of the real estate owners being unaffected by the tax on capital gain ($Tax = 0$), notably because the tax scheme takes into account the holding period, and an overall average value of 3.9% that reaches 7.7% conditional on being non null with a standard deviation of 4.6%. To get a sense of these rather high values, one may keep in mind that real estate prices have been multiplied by 2.5 in real terms between 1998 and 2008.

Frictions and relocation

We proceed in two steps. In the first step, we run various cross-section regressions to show that higher relocation costs, as proxied by the tenure status or, for owning firms, by the latent capital gains, are indeed associated with a lower propensity to relocate. More precisely, we run the following specification for firm i 's decision to relocate:

$$z_i = \mu_1 Te_i + \mu_2 X_i + \varepsilon_{i,s,d}, \quad (4.17)$$

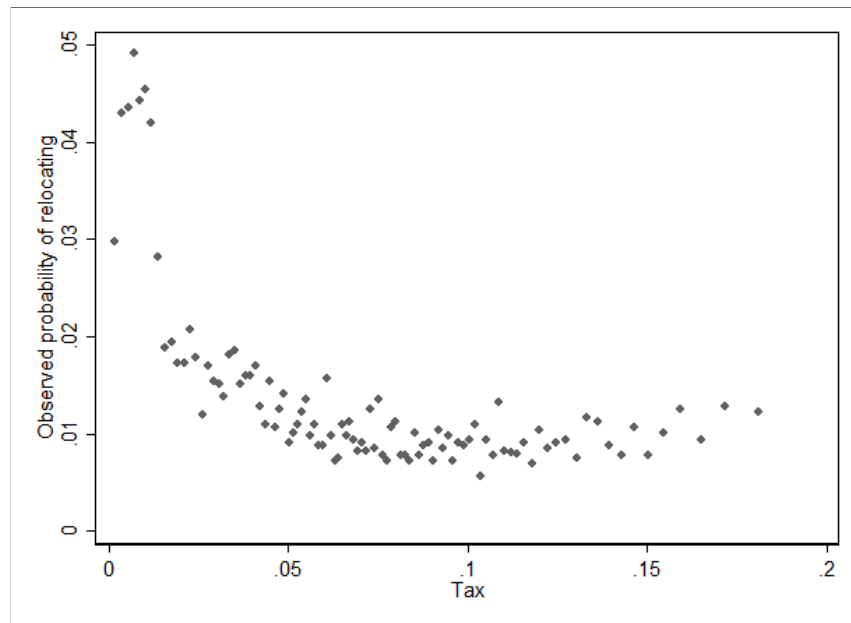
where Te_i is our dummy equal to 1 if the firm reports real estate holdings in initial year of observation. We also consider:

$$z_i = \beta_1 Tax_i + \beta_2 X_i + \varepsilon_{i,s,d}, \quad (4.18)$$

where Tax_i has been defined previously. This regression is close to the theoretical results shown in Figure 4.3. In Figure 4.11 we plot the observe probability to relocate and the average value of the variable Tax for each percentile of the distribution of Tax . We find a downward curve that shows the same shape as the one in Figure 4.3.

The estimation results can be found in Table 4.5: column 1 corresponds to the model presented in equation (4.17) while columns 2 to 6 correspond to model defined by equation (4.18). As directly depends on the volume of real-estate.

Fig. 4.11: Propensity to relocate and relocation costs as measured by the latent tax on capital gains



Notes: *Tax* denotes the share of the proceeds from a potential real estate sale that must be paid as a tax on capital gains. We separate each observations into 100 percentiles of *Tax* and plot the within percentile share of relocating firms. Period of observation: 1994-2013. Source: FiBEⁿ, see Appendix C.1 for more details about the data.

previously, we control for the age and the size of the firm and a *département* × sector fixed effect is added. In columns 3 and 4, we also add covariates capturing the age and the volume of the premises owned by the firm, both of which having direct influence on the propensity to relocate. Column 5 adds a *département* × first year of observation fixed effect.

From column 1, we see that a real estate owning firm has a 0.6 percentage points lower yearly propensity to relocate than an otherwise observably similar renting firm.

In columns 2 to 5, the main coefficient of interest is the one associated with *Tax*, the share of the proceeds from the real estate asset sales that would be paid under the heading of the “tax on capital gains”. As explained above, this share results from a marginal tax rate, identical across firms, and a tax base, that varies across firms and across time. The variability of the tax base across firms and across time results from heterogeneity in the acquisition dates and in the dynamics of local prices since the acquisition. Results suggest that a one standard deviation

Table 4.5: Relocation cost and relocation choice - Cross section OLS

Dependent variable: Relocate						
	All	Owners				
	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Owner	-0.597*** (0.036)					
Tax		-2.248*** (0.491)	-2.417*** (0.498)	-2.666*** (0.561)	-2.891*** (0.579)	-2.180*** (0.588)
Age	-0.022*** (0.001)	-0.014*** (0.001)	-0.013*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.007*** (0.001)
Size	1.740 (1.746)	5.352* (2.899)	5.314* (2.902)	5.050* (2.986)	5.041* (2.857)	5.029* (2.863)
Volume Real Estate			-0.018*** (0.005)	-0.006 (0.005)	-0.004 (0.005)	-0.003 (0.005)
Age Real Estate				-0.024*** (0.005)	-0.023*** (0.005)	-0.021*** (0.005)
R ²	0.087	0.121	0.121	0.121	0.160	0.160
Observations	118,980	45,181	45,181	44,412	44,412	44,412

Notes: Variables definitions are given in Table C.3. Column 1 uses all firms while columns 2 to 5 restrict to real estate owners. The dependent variable, Relocate, is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Other variables are taken in the first year of observation. Regressions include a *département*×*sector* fixed effect. Column 5 adds a *département*×*first year of observation* fixed effect. Column 6 uses an alternative proxy for the latent tax on capital gain built from national price level. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

increase in this tax share is associated with a 0.8 to 0.9 percentage point reduction in the propensity to relocate among real estate owning firms.

One may be concerned that the level of the latent tax on capital gains is correlated with unobservable growth prospects and that the distributions of changes in productivity is affected by the level of these latent capital gains. However, because the latent capital gains are growing with the positive change in local real estate prices, we are expecting that the higher the latent capital gains, the better the local economic conditions and the more likely the firms are to relocate. We hence argue that any correlation between the latent capital gains and unobservable

growth prospects upward bias our coefficient of interest and that the negative effect of the latent tax on the propensity to relocate is an upper bound. In addition, in column 6 of Table 4.5, we replace variable Tax by another proxy constructed in the exact same way as Tax , but using an index of real estate prices computed at the national level, excluding the area where the firm is based.²²

Another potential concern is that the latent tax on capital gains is in fact capturing many different features, and namely the fact that it mechanically decreases with the age of real-estate. However, when moving from column 2 to column 5 of Table 4.5, the coefficient on the latent tax variable is stronger (in absolute value) as we add more control variables on the nature of the real estate.

Finally, to control for firm specific characteristics that are unobservable with our data, we run a panel fixed effects model. In terms of timing, the dependent variable, $z_{i,t}$ is a binary variable equal to 1 if the firm has relocated locally between t and $t + 1$ and the variable $Tax_{i,t}$ is computed at the end of the year. Results are presented in Table 4.6 and are consistent with what was found in the OLS estimation of the cross-section model.

All these results speak to the intuitive idea that relocation costs dampen the firms' propensity to relocate. By highlighting the role of the latent tax on capital gains, they provide empirical evidence to support our model. They also echo those of the existing literature that emphasized the "lock-in" effect of the tax on capital gains (see for example Yitzhaki, 1979; Feldstein et al., 1980 or Kanemoto, 1996).

²²Formally, we use formula (4.16) where we replaced p_t^d by $\tilde{p}_t^d = \sum_{\delta \neq d} w^\delta p_t^\delta$, with w^δ being a weight associated with *département* δ based on its population. See Table C.15, for more results using this alternative definition of the tax on capital gain.

Table 4.6: Relocation cost and relocation choice - Panel Fixed-Effect results

Dependent variable: Dummy for having relocated at t					
	Owners (1)	Owners (2)	Owners (3)	Owners (4)	Owners (5)
Tax $_{t-1}$	-0.181*** (0.007)			-0.179*** (0.010)	-0.168*** (0.009)
Tax $_{t-2}$		-0.120*** (0.006)		-0.001 (0.009)	-0.008 (0.009)
Tax $_{t-3}$			-0.067*** (0.005)	-0.007 (0.007)	0.001 (0.007)
Age	0.001*** (0.000)	0.001 (0.001)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Size	-0.015 (0.017)	-0.030 (0.020)	-0.030 (0.025)	-0.022 (0.024)	-0.024 (0.024)
Real Estate Age	-0.003*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Real Estate Volume	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
R ²	0.152	0.160	0.161	0.164	0.164
Observations	295,718	272,414	248,142	248,142	248,142

Notes: Variables definitions are given in Table C.3. The dependent variable is a binary variable equal to 1 if the firm has locally relocated (with a distance below 15km) between t and $t + 1$. Regression includes a firm fixed effect and a sector times year fixed effect. Column 5 uses an alternative proxy for the latent tax on capital gain based on national price level. Panel fixed effect OLS regression with robust standard errors clustered at the *département* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Direct effect of relocation costs

We now turn to our second step where we explore the effect of the relocation costs on employment dynamics though its direct negative effect on the propensity to relocate. Our model predicts that the relationship between relocation costs and employment growth differ across the distribution of productivity shocks.

As in Table 4.3, we run cross-section *OLS* regressions where the dependent variable is the

average employment growth over the observed time period. As in Table 4.5, we focus on the two distinct sources of heterogeneity with regard to relocation costs. Specifically, we estimate the following equation:

$$\Delta l_i = \mu Te_i + \mu_2 X_i + \varepsilon_{i,s,d}, \quad (4.19)$$

where Te is, as previously, a binary variable equal to 1 if the firm owns its real estate and $\varepsilon_{i,s,d}$ contains an idiosyncratic error term and a *département*-sector fixed effect. Restricting our sample to owning firms, we also estimate:

$$\Delta l_i = \beta_1 Tax_i + \beta_2 X_i + \varepsilon_{i,s,d}. \quad (4.20)$$

Results can be found in Table 4.7. Columns 1 and 2 report estimates of equation (4.19) and restrict attention respectively to growing and declining firms. We include our usual set of control variables considered in the first year the firm appears in the sample. For growing firms, we find that holding real estate assets is associated with a mean employment growth lower by almost 1 percentage point as compared to similar renting firms. For declining firm, the estimate is positive but smaller in magnitude (around 0.2). We turn to the model presented in equation (4.20) using the latent tax on capital gains. Results are presented in columns 3 and 4, where we have also added covariates to control for the age and volume of owned real estate assets. We observe that the latent tax on capital gains has a negative effect for growing firms. A one standard deviation reduction in the (latent) share of the proceeds from the premises' sales that would be paid as a tax on capital gains is associated with an increase of 0.25 percentage point in yearly employment growth for growing firms. Finally, notice that the fact that the latent tax on capital gains is only paid in the case of a relocation, it is unlikely that it has any other direct effects on the employment growth once we control for any local dynamism through

département-sector fixed effects.

Just like previously, we estimate the same equation (4.20) using a quantile regression model. The results, presented in Figure 4.12, is consistent with what we described above and the prediction of the model: relocation costs have a negative effect on employment for growing firms and a positive effect for declining firms.

Overall, relocation costs have a negative effect on employment. We can show this by taking advantage of our panel and we run the following model for various value of k :

$$\Delta l_{i,t} = \beta_1 Tax_{i,t-k} + X_{i,t}\beta_2 + \varepsilon_{i,s,d,t}. \quad (4.21)$$

Just like previously, $\varepsilon_{i,t,s,d}$ includes fixed effects at the sector times year level (s, t) a firm fixed effect and an idiosyncratic error. We allow for correlation of this error terms within firm. Results are shown in Table 4.8 and confirm our previous findings even after controlling for any firm specific unobserved time-invariant characteristics.

4.4.3 Implication in terms of misallocation

Our results suggest that frictions in the real-estate market generate a suboptimal allocation of premises volume and in turns of workforce due to the complementarity between the two inputs. To illustrate this, we construct a measure of misallocation based on [Olley and Pakes \(1996\)](#) and following [Duranton et al. \(2015\)](#), by calculating the covariance between the market share of a firm and its labor productivity level. We should expect that areas in which the real estate market is more constrained have a higher misallocation of inputs. In Figure 4.13, we have plotted the misallocation index against the share of firms that are real-estate owners for each *département*. The correlation between the two is clearly positive.²³ As in [Hsieh and](#)

²³In Figure 4.13, we show results for the year 1994 but using another year or pooling all years together show similar upward slopping fitting line.

Table 4.7: Relocation costs and employment dynamics - Cross section results

Dependent variable: Yearly average employment growth (in %)						
	Growing	Declining	Growing	Declining	Growing	Declining
	(1)	(2)	Owners	Owners	Owners	Owners
	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Owner	-0.987*** (0.149)	0.228*** (0.046)				
Tax			-4.855** (2.309)	-0.243 (0.767)	-5.260** (2.390)	-0.127 (0.737)
Age	-0.076*** (0.007)	0.010*** (0.001)	-0.035*** (0.008)	0.006*** (0.002)	-0.035*** (0.008)	0.006*** (0.002)
Size	-3.309 (2.059)	4.187*** (1.531)	-2.680 (6.220)	9.785** (4.085)	-2.732 (6.221)	9.785** (4.082)
Age Real Estate			-0.087*** (0.024)	-0.003 (0.007)	-0.089*** (0.024)	-0.003 (0.007)
Volume Real Estate			0.078 (0.055)	-0.034** (0.017)	0.079 (0.055)	-0.034** (0.017)
R ²	0.105	0.216	0.243	0.310	0.243	0.310
Observations	72,375	46,605	24,855	19,557	24,855	19,557

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. All covariates are taken in the first year the firm appears in the database. Columns 1, 3 and 5 (resp. 2, 4 and 6) restrict to firms with positive (resp. negative) employment growth over the period of observation. Columns 3 to 6 in addition restrict to real estate owning firms. Regressions include the number of years of observation for each firm and a sector times *département* fixed effect. Columns 5 and 6 uses a proxy for the tax on capital gain based on real-estate prices at the national level. Cross section OLS regression with robust standard errors clustered at the *département* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

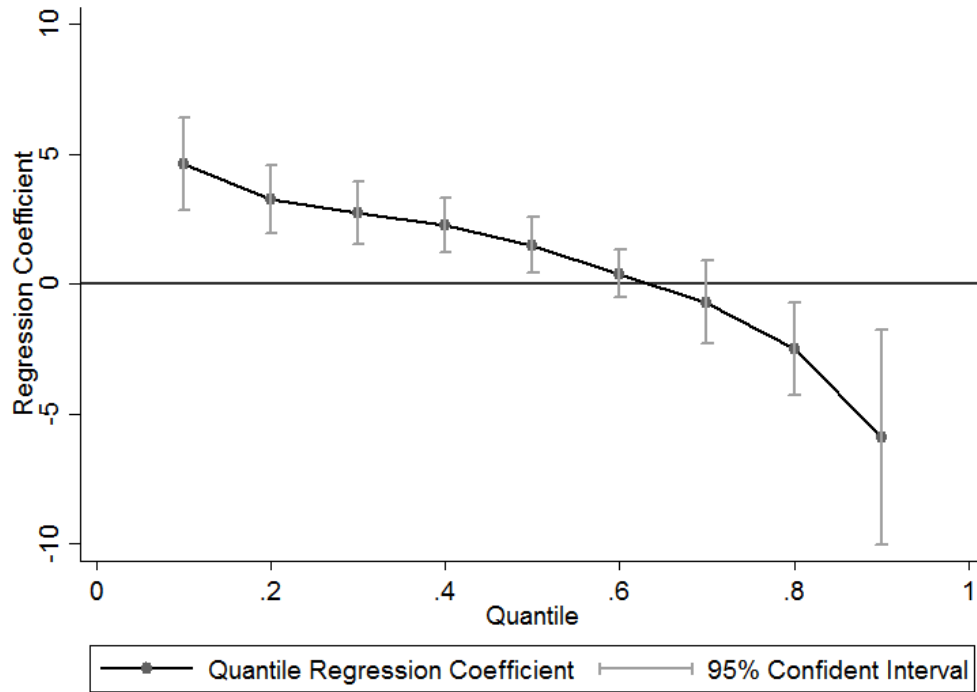
Klenow (2009), misallocation induced by the distortion of the real estate market account for a reduction in aggregate productivity and consequently in aggregate output.

Table 4.8: Relocation costs and employment dynamics - Panel Fixed-Effect results

Dependent variable: employment growth at t (in %)				
	Owners (1)	Owners (2)	Owners (3)	Owners (4)
Tax $_{t-1}$	-13.732*** (1.717)			-6.522*** (2.384)
Tax $_{t-2}$		-11.709*** (1.316)		-5.811** (2.434)
Tax $_{t-3}$			-8.192*** (1.517)	-2.199 (2.146)
Age	-0.220** (0.096)	-0.121 (0.110)	-0.275** (0.110)	-0.268** (0.110)
Size	-0.112*** (0.025)	-0.115*** (0.025)	-0.135*** (0.030)	-0.133*** (0.030)
Real Estate Age	-0.247*** (0.022)	-0.192*** (0.017)	-0.152*** (0.018)	-0.184*** (0.021)
Real Estate Volume	0.142*** (0.036)	0.107*** (0.026)	0.100*** (0.025)	0.099*** (0.025)
Observations	424,912	381,535	338,238	338,238
R ²	0.155	0.167	0.171	0.171

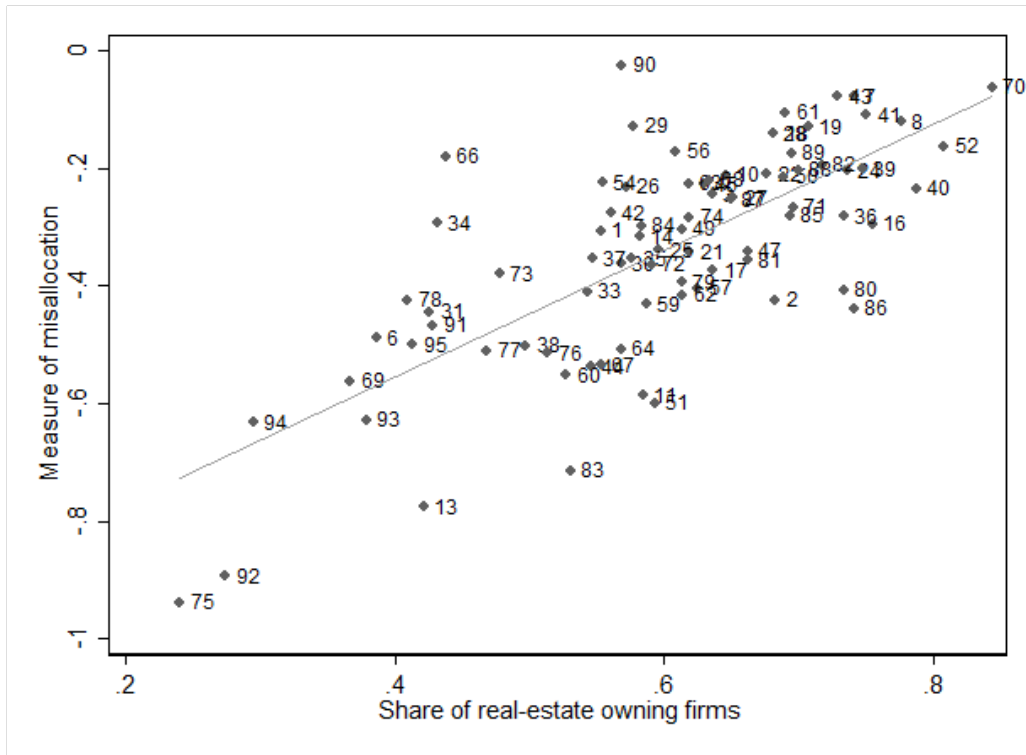
Notes: Variables definitions are given in Table C.3. Regression includes a firm fixed effect and a sector times year fixed effect. Panel fixed effect OLS regression with robust standard errors clustered at the firm level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Fig. 4.12: Relocation costs and employment dynamics.



Notes: This graph plots the coefficients on the latent tax on capital gain (Tax) from a cross-section quantile regressions with employment growth as a dependent variable (equation (4.17)) residualized on a *département*-sector fixed effect. We plot the coefficient obtained for each of the quantile: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9 along with the 95% confidence interval. Regression also includes our usual control variables: Age, Size, Age and Volume of real-estate (all taken in the first year of observation). Confidence intervals at the 95% level have been estimated with a variance-covariance matrix built with 40 bootstrap replications.

Fig. 4.13: Relocation frictions and misallocation



Notes: This graph plots the measure of misallocation presented in subsection 4.4.3 against the share of real-estate owning firms in each *département* in 1994. *département* codes are explained in Table C.1. Source: FiBEn, see Appendix C.1 for more details about the data.

4.5 Conclusion

This chapter derives the theoretical implications of adjustment costs of real estate assets on firm level factors' demand and explores the empirical relevance of the derived theoretical prediction.

First, we build a general equilibrium model in which firms make decisions on inputs' adjustment following productivity shocks against a background of fixed adjustment costs of real estate induced by relocation. The model predicts that a relocation is associated with a concomitant adjustment of employment level. The magnitude of those adjustments may differ whether the firm is growing or slackening; the relocation of a growing firms being typically associated with larger change in the workforce. Our model also predicts that relocation costs reduce the propensity to relocate and distort the employment growth distribution with a particularly marked negative impact on firms facing positive productivity shocks.

Second, we confront these predictions to the data using a large dataset on French firms over the period 1994-2013 and taking advantage of the firm-level heterogeneity in the real estate adjustment costs entailed by the latent tax on real estate capital gains. All the results derived from the theoretical framework are confirmed. Relocating is associated with significant adjustment in the workforce size and the level of the adjustment costs reduces the propensity to relocate, and constrains jobs creation of the growing firms.

This chapter documents an example of costs that prevent the optimal adjustment of inputs across firms following productivity shocks and provides evidence of their effect on misallocation of inputs across firms.

CHAPTER 5

Conclusion

The three chapters of this thesis have explored different aspects of firms' response to different stimuli, from an increase of R&D intensity to an export demand or productivity shock. More specifically, we first looked at how an increase in research expenditure translate to workers' wage and to organizational changes a firm. We have then explored how an exogenous demand shock, namely an increase in export markets' demand size, generates an heterogeneous response in terms of innovation depending on the productivity level of the firm. Finally, we have study how factor adjustment costs can impair the dynamic response to a productivity shock and have sizable macroeconomic effects, considering the special case of corporate real-estate.

All in all, these three chapters help to understand how firms grow and what drive differences in size distribution of firms across countries that are emphasized in the literature (see [Hsieh and Klenow, 2009, 2014](#)).

The availability or more comprehensive microdata and appropriate statistical softwares have open many avenue to further investigate the questions and puzzles associated with firms' dynamics. Throughout the different chapters of this thesis, we have suggested ways of exploring further questions. First, regarding the link between international trade and growth, it would be interesting to further exploit the geographical dimension of patent data to look at how technological spillover positively affect firms' decisions (in the spirit of [Bloom et al., 2013](#)). Another interesting avenue following the third chapter would be to consider the potential effect of adjustment costs and regulation on innovation, taking advantage of the numerous changes and discontinuities offered by the constraints on firms' size (see [Garicano et al., 2016](#)). A last

interesting avenue we would like to emphasize concern misallocation and job reallocation, which is a latent question in all three chapters. Innovation shocks have major implication in terms of labor adjustments: in the first chapter, we see that more innovative firms tend to outsource more non complementary low skill occupations and second chapter shows that the least productive firms will be negatively affected by an export shock in terms of their productivity and size. For these mechanism to have aggregate positive effects, they must be accompanied by a flexible labor market, which is a consequence of the results of the third chapter.

All these questions are left for further research.

Appendices

APPENDIX A

Appendix of Chapter 1

A.1 Data construction and additional description

This appendix describes the construction of our main sample which results from the merge of two datasets provided by the ONS: the Annual Survey of Hours and Earnings (ASHE) and the Business Expenditures on Research and Development (BERD).

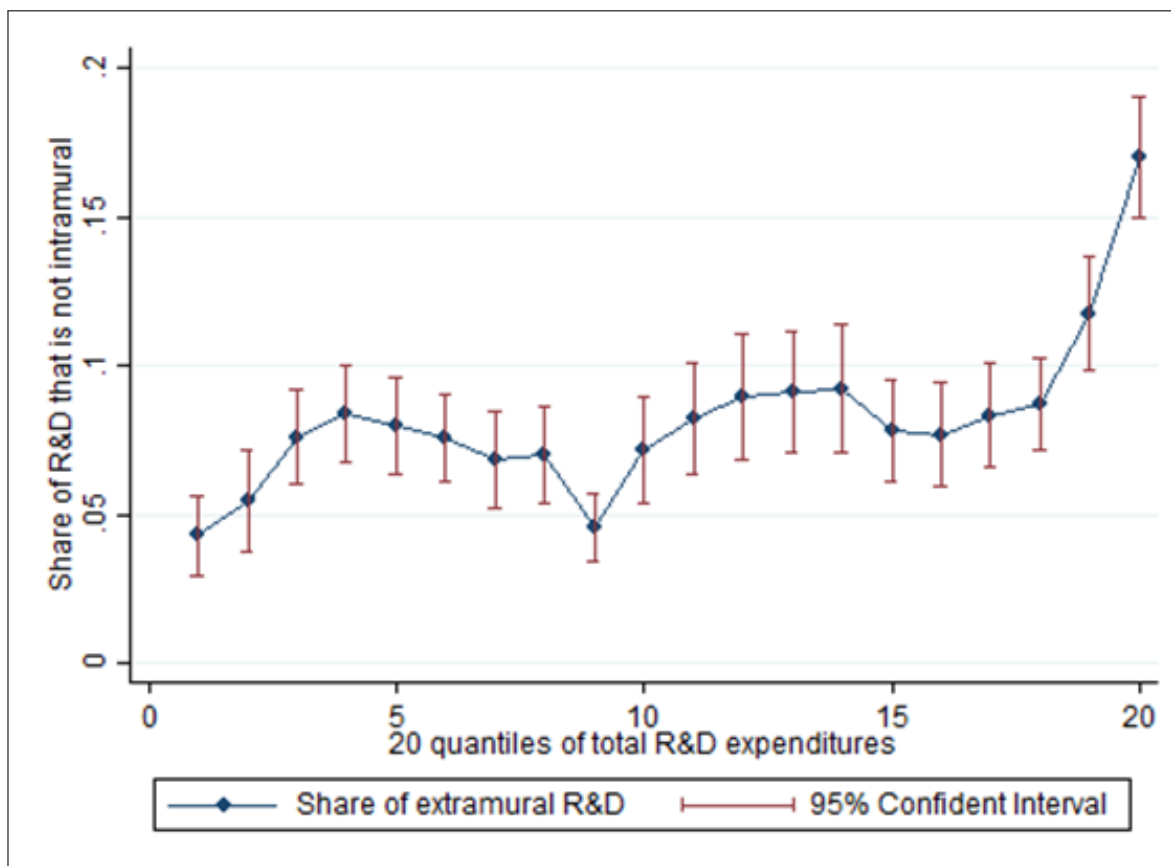
A.1.1 Business Expenditures on Research and Development

The Business Expenditures on Research and Development (BERD, [Office for National Statistics, 2016b](#)) is an annual survey conducted by the Office of National Statistics (ONS) that collects information on R&D activities of businesses in the United Kingdom. It is a stratified random sample from the population of firms that conduct R&D. The selected firms then receive a form asking them to detail their innovative activities in accordance to the OECD's Frascati Manual guidelines (see [OECD, 2015](#)). The stratification scheme has changed over time, but includes a census of firms with over 400 employees. These are the firms we are interested in. The BERD data is available from 1994-2014 with a coverage that is consistent since 2000.

BERD records expenditure at the level of the firm, the product that the R&D is related to, and the establishment carrying out the R&D. We also know whether R&D was carried out in house (intramural) or outsourced (extramural). Product is recorded at the level of 33 categories. We know the split between civil and defense. More than 99% of the sampled firms report

R&D for only one product, representing 75% of total intramural expenditures and 69% of extramural expenditures. 88.2% of intramural R&D expenditure and 96.5% of extramural R&D is civilian; 10% of firms that report doing some R&D do at least some defense R&D. Total R&D expenditures are the sum of intramural and extramural R&D at the firm level. In the chapter, we refer to the level of R&D “R&D expenditures” and the level of R&D divided by the number of employees in the firm as “R&D intensity”. Including extramural R&D is important as many large firms outsource a large part of their R&D activities, see Figure A.1, and this varies across industries.

Fig. A.1: Outsourced R&D expenditures for 20 quantiles of total R&D intensity



Notes: Outsourced (extramural) R&D expenditure is divided by total R&D expenditure (extramural and intramural). Quantiles of total R&D expenditures are computed each year on the sample of firms that have been matched to ASHE and that contains more than 400 employees (see subsection A.1.4).

Table A.1 reports the average amount of intramural and extramural R&D across 20 quantiles of

Table A.1: Distribution of employment and R&D

Quantile of R&D	Employment	Intramural R&D	Extramural R&D	Number of firms
0 (no R&D)	2,401	0	0	27,183
1	8,172	71	5	390
2	4,480	215	14	384
3	2,932	282	23	383
4	2,521	338	59	387
5	2,829	638	73	383
6	1,643	512	55	384
7	1,963	814	72	386
8	1,749	1,015	98	384
9	1,349	1,008	110	384
10	1,727	1,609	218	381
11	1,629	2,012	231	387
12	1,888	3,136	387	383
13	1,523	3,249	335	385
14	1,455	4,328	387	386
15	1,629	6,749	435	382
16	2,471	16,163	840	386
17	2,668	24,990	1489	386
18	2,314	35,573	2903	383
19	2,513	62,948	9973	384
20	2,290	140,127	70213	380

Notes: This table presents the average number of employees, average expenditures in intramural R&D (in thousand pounds) and average expenditures in extramural R&D (in thousand pounds) for 20 quantiles of R&D intensity (defined as the sum of intramural and extramural R&D expenditures per employee). The first categories “0 (no R&D)” corresponds to firm that do not report R&D in the current year. Quantiles of R&D are computed each year on the sample of firms that have been matched to ASHE and that contains more than 400 employees (see subsection [A.1.4](#)).

the distribution of total R&D intensity.¹ The distributions of both intra and extramural R&D are highly skewed, firms in the highest vintile are very different from others.

A.1.2 Annual Survey on Hours and Earnings (ASHE)

The Annual Survey of Hours and Earning (ASHE, [Office for National Statistics, 2016a](#)) is a 1% random sample of the UK workforce based on the last two digits of the national insurance numbers. We use data from 2004 to 2014.² The level of observation in ASHE is the individual

¹Quantiles of R&D are computed each year, so firms can move between quantiles.

²There is a discontinuity in ASHE in 2004.

job, however, over 98% of individuals have only one job at any point in time, so appear only once per year in the dataset. We have a total of over 1,850,000 observations on around 340,000 individuals working in around 158,000 enterprises.³

A.1.2.1 Cleaning

We clean the data and remove observations: with a missing individual identifier (variable *piden*), with a missing firm identifier (variable *entref*) or those not coded with an adult rate marker (variable *adr*), which mostly involves removing trainees from the sample. We keep only the main job for each individual. This cleaning removes 4.2% of observations. The version of ASHE we use is a panel where individuals are uniquely identified by their (transformed) national insurance number. However, a problem occurs with temporary national insurance number that are reused for different people. We drop all individuals that change gender or change birth dates: 1.2% of observations are affected and dropped. We delete individuals where the data are clearly miscoded, e.g. their age that is less than their tenure in the firm, and we drop individuals aged less than 18 or older than 64 (around 2% of total observations). The outcome of this cleaning is a database of more than 1,650,000 observations on around 320,000 individuals working in 140,000 enterprises. We call this database “Clean ASHE”.

A.1.2.2 Individual income

There are various measures of income in ASHE. Gross weekly wage is collected during the survey period (from one to four weeks) in April of each year. This is reported by the employer and is considered to be very accurate. The gross weekly wage can be broken down into basic pay, incentive pay, overtime pay, additional premium payment for shifts that are not considered overtime and additional pay for other reasons. The gross weekly wage does not include any

³An enterprise can be a private corporation, public company, government agency, non profit organisation, etc.

capital income such as stock-options (reported “incentive pay” includes profit sharing, productivity, performance and other bonus or incentive pay, piecework and commission.). The number of hours worked are reported, split between overtime and basic paid hours. ASHE also provides data on gross annual earnings, as well as the share of this earning that is an incentive payment.

We define hourly income as the ratio of gross weekly wage divided by total number of paid hours (including overtimes). This is the measure of income we will consider as a baseline but we also show descriptive statistics for gross annual earnings. Including other types of income and incentive payments is arguably relevant especially in the case of very high incomes as shown by [Bell and Van Reenen \(2013, 2014\)](#). We study the sensitivity of our results to including or excluding additional types of income in the basic pay in section [A.4.1](#).⁴

A.1.2.3 Skills classification

We use a classification based on a match between the National Qualification Framework (NQF) and the Standard Occupation Code (SOC).⁵ The NQF defines 8 levels of skill based on the required qualification from PhD (level 8) to Entry level (less than GCSE grade D-G). The current UK immigration rules use 6 groups (see [Table A.2](#)).⁶

Note that there is another possible classification of skills, based on the standard occupational classification (SOC). Skills here are defined as “the length of time deemed necessary for a person to become fully competent in the performance of the tasks associated with a job”. Level 4 corresponds to the highest skill level and includes Corporate Managers, Science and technology professionals, Health professionals, Teaching and research professionals and Business and public service professionals. Level 1 corresponds to the lowest skill level and includes

⁴The share of incentive pay increases strongly with earnings, while the share of overtime pay is stable around 5% for the first three quarters of the income distribution, and decreases with wage for the remaining top quarter.

⁵See for example the “code of practice for skilled work, Immigration Rule Appendix J”.

⁶A few specific occupations, which we don’t use in our analysis, are unclassified: clergy, military, elected officers, sports players and coaches and prison service officers.

Table A.2: Skill classification

Skill category	Description
Low skill	
Skill cat 1	Lowest skill occupations, includes many manufacturing basic occupations, child-care related education, housekeeping, telephone salespersons
Skill cat 2	corresponds to a NQF below 3 but not considered as an entry level. Occupations such as pharmaceutical dispensers, greenkeepers, aircraft maintenance technician
Intermediate skill	
Skill cat 3	Requires a NQF of 3 which corresponds to a Level of Advanced GCE (A-level). This category spans many different occupations from Fitness instructors to Legal associate professionals.
Skill cat 4	Requires a NQF of 4 and above which corresponds to a Certificate of Higher Education. It includes many technical occupations like Medical technicians or IT operations technicians and some managerial occupations.
High skills	
Skill cat 5	Includes most managerial and executive occupations as well as engineers. These occupations require at least a NQF of 6 which corresponds to a Bachelor's degree or a Graduate Certificate.
Skill cat 6	Corresponds to occupational skilled to PhD-level and include most scientific occupations like Chemical scientists, Biological scientists, Research and development manager but also Higher education teaching professionals.

Notes: This table describe the education requirement for each of our six skill categories. These requirements have been taken from the “code of practice for skilled work, Immigration Rule Appendix J”.

elementary trades, plant and storage related occupations and elementary administration and service occupations.

This classification relies on the first two digits of the 4-digit SOC code. Its main advantage is that it is very straightforward to implement and it is consistent in time. Indeed, although the SOC changed its classification in 2000 and 2010, the first two digits remain unchanged. However, one disadvantage is that relying on the first two digit is not accurate enough to distinguish between, for example, a restaurant manager (SOC2010 code 1223) and a natural environment and conservation manager (SOC2010 code 1212). But according to the work of [Elias and Purcell \(2004\)](#), the former group counts 9.5% of people aged 21-35 and holding a first degree or higher whereas the latter counts 72% of them. This analysis uses on the labor Force Survey 2001-2003. In another article, [Elias and Purcell \(2013\)](#), they advocate the use of another classification and consider the restaurant manager group as a “non graduate group” and the natural environment manager as an “expert group”.

Tables [A.3](#) and [A.4](#) show that these workers have different labor market participation behaviour and different outcomes in the labor market.

A.1.3 Travel to work areas

A labor market is defined as a travel to work area and there are around 240 such areas in the UK depending on the year.⁷ Since 2011, there are exactly 228 travel to work areas (TTWAs) in the UK with 149 in England, 45 in Scotland, 18 in Wales, 10 in Northern Ireland and 6 cross-border. This is a tool widely used by geographers and statisticians although they have no legal status. They are defined as a form of Metropolitan Area and intent to group urban areas and their commuters hinterland. London, Bristol and Manchester are examples of Travel To Work Areas.

⁷Definition of travel to work areas change in time. For this reason, we never use a travel to work area continuously in time.

Table A.3: Demographics by skill level

	Obs.	Hours	% Work full-Time	% Male	Age	Tenure
Low skill						
Skill cat 1	338,102	30.2	60	49	37.3	6.2
Skill cat 2	35,959	35.5	83	68	39.2	8.2
Intermediate skill						
Skill cat 3	71,231	36	88	60	39.1	9.3
Skill cat 4	24,740	36.4	93	60	39.5	9
High skill						
Skill cat 5	102,539	36.4	95	70	40.7	9.8
Skill cat 6	3,284	35.8	92	62	39.3	10.4
Total	575,855	32.6	73	56	38.4	?

Notes: Skill categories are based on occupation codes as described in [A.1.2.3](#).

Table A.4: Pay by skill categories

Skill	Hourly pay	Weekly pay	% incentive	% overtime	Annual earnings
Low skill					
Skill cat 1	8.58	285.29	2.59	5.66	13,659
Skill cat 2	11.54	444.87	2.23	5.45	21,948
Intermediate skill					
Skill cat 3	13.52	504.32	5.23	3.61	25,840
Skill cat 4	16.83	625.04	5.23	2.19	32,904
High skill					
Skill cat 5	25.45	931.56	7.67	1.46	53,978
Skill cat 6	22.25	804.11	6.24	1.10	43,542
Total	12.82	455.98	?	?	23,900

Notes: Skill categories are based on occupation codes as explained in subsection [A.1.2.3](#).

Table A.5: Construction of the sample

ASHE	Observations	Individuals	Mean wage	Sd wage
Raw ASHE	1,841,495	341,463	13.0	43.1
Clean ASHE	1,655,627	323,409	13.3	14.3
Private Corporations	977,236	230,501	12.9	16.3
Final Sample	573,299	148,503	12.8	16.7
BERD	Observations	Firms	% intramural R&D	% extramural R&D
Raw BERD	216,957	48,554	100	100
400+ Employees	8,086	1,782	75.1	84.0
Final Sample	7,703	1,767	66.1	77.9

Notes: This table presents the evolution of the two databases ASHE and BERD across the successive steps conducted to match them. **ASHE:** Raw data corresponds to the standard ASHE database 2004-2014. Clean ASHE corresponds to the database “Cleaned ASHE” as described in subsection A.1.2.1. Private corporation corresponds to “Clean ASHE” restricted to private corporations and Final corresponds to “Clean ASHE” restricted to private corporations with more than 400 employees. Mean wage is measured as the average total weekly earning. **BERD:** Raw data corresponds to the standard BERD database 2004-2014. 400+ employees corresponds to this database restricted to firm with more than 400 employees and Final corresponds to firms of more than 400 employees that matched the final version of ASHE. % of intramural and extramural R&D are measured with respect to Raw data.

A.1.4 Matching BERD and ASHE

We match the individuals in “Clean ASHE” with the firms they work for in BERD; we restrict attention to private corporations (dropping public corporations, charities, unincorporated firms, etc). We start with all individuals in “Clean ASHE” who work for a firm with 400 or more employees and match them to the population of firms in BERD with 400 or more employees. Our final sample includes around 580,000 observations on around 150,000 individuals working in around 6,300 different firms; there are around 31,000 firm-year combinations. The implication of the matching and exact numbers can be found in Table A.5 and the outcome of merging the subsample of firms in BERD over 400 employees and private firms in ASHE over 400 employees is presented in Table A.6.

We use information on firms with more than 400 employees. These firms differ from smaller ones in some ways that are shown in Table A.5. However, the distribution of wage in this

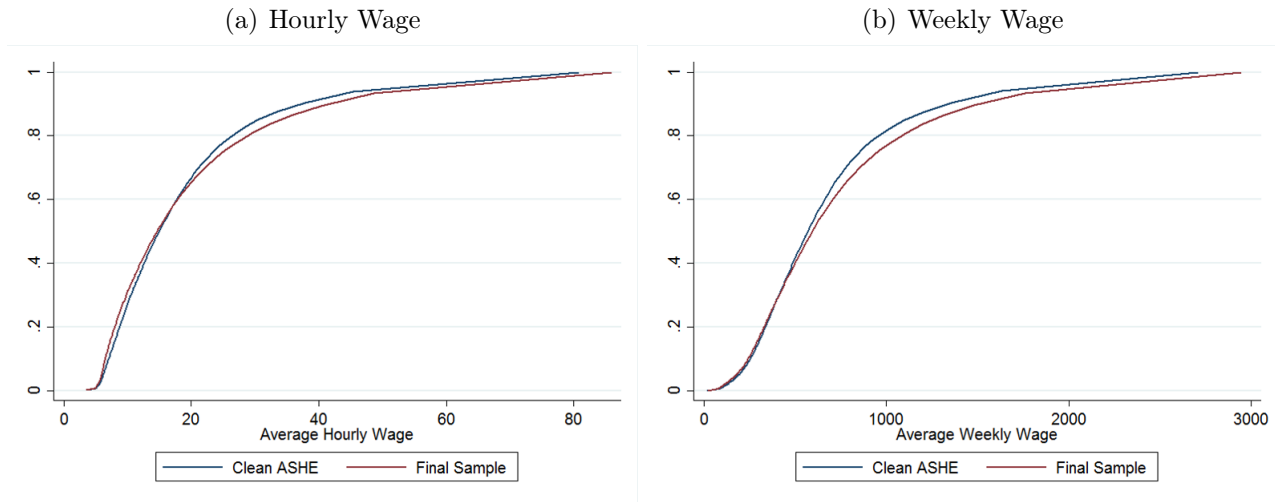
Table A.6: Matching results at the firm-year level

Year	in BERD not in ASHE	in ASHE not in BERD	in BERD and ASHE
2004	102	2,406	670
2005	91	2,377	808
2006	91	2,339	956
2007	102	2,372	757
2008	96	2,408	628
2009	75	2,370	798
2010	86	2,322	696
2011	97	2,372	708
2012	97	2,435	781
2013	108	2,488	799
2014	109	2,612	844

Notes: This table presents the number of firms that did not match because they are in BERD but not in ASHE (column 1) or because they are in ASHE but not in BERD (column 2) and the firms that are both in BERD and ASHE (column 3).

sample is very similar to the one in the total sample, as seen in Figure A.2. The geographical coverage of these firms is also very similar.

Fig. A.2: Cumulative distribution function of log wage



Notes: This figure plots the empirical cumulative distribution function for two samples: Clean ASHE, corresponding to the 1% random sample of the British population without restriction (other than some cleaning described in Appendix A.1.2) and Final Sample corresponding to workers of private companies with more than 400 employees.

Table A.7: Variable description

Variable name	Description
Age	Age of the individual at the time of the survey in year
Tenure	Number of year spent in the firm by the individual
Male	Dummy for being a male
Full Time	Dummy for working more than 25 hours a week on average
Age2	Age squared
Tenure2	Tenure squared

Notes: This table presents the description of the main variables used in the regressions.

A.1.5 Descriptive statistics

Table A.7 gives description of the variables used in the regressions throughout the chapter while A.8 shows statistical moments of the main variables of interest at the individual level. Low skill workers represent the majority of workers in our sample (59%)⁸, see Table A.3. Workers with higher skill level earn higher wages with the exception of skill category 6 (researchers and professors), where the average is below the average for category 5. We also see from Table A.4 that more innovative firms have on average a larger proportion of high skilled workers.

A.1.6 O*NET data

The O*NET dataset is a database aiming at providing an accurate definition of each occupations in the US at a very detailed level. Information include the type of tasks, the skills and abilities usually required and many characteristics such as, for example, the level of exposition to noise.

The database is freely available from the dedicated website⁹ and we use the version 21.1 Database - November 2016 Release.

The information have been gathered either from interviewing workers or from experts descrip-

⁸This is a slightly larger proportion than when considering the share of low skilled worker in the whole “clean ASHE” dataset (48%).

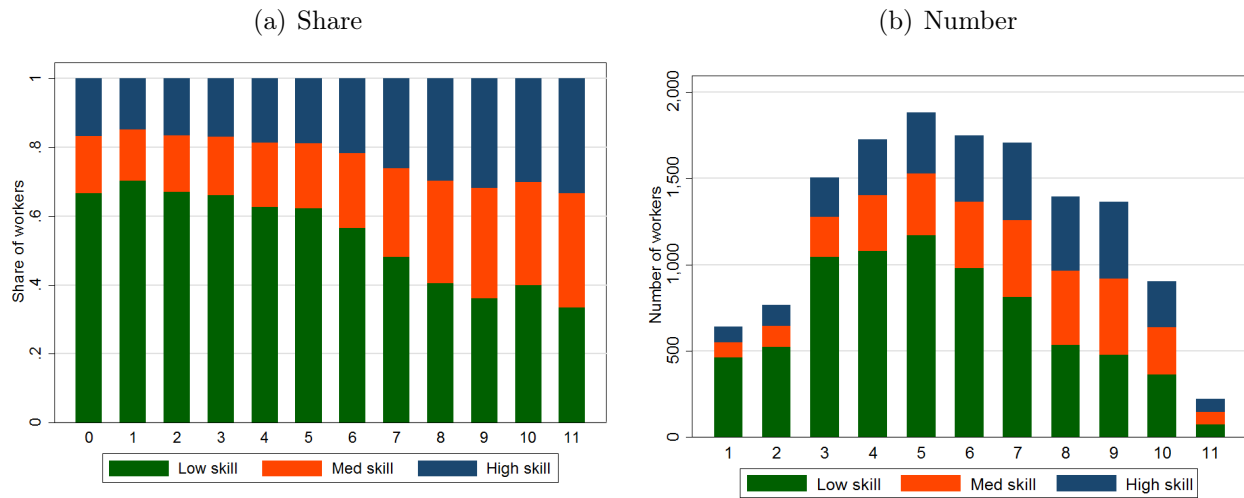
⁹<http://www.onetcenter.org/database.html>

Table A.8: Descriptive statistics of wage variables

Variable	Mean	sd	p10	p25	p50	p75	p90	p99
Total hourly wage (£)	13.5	14.5	6	7.1	10	15.5	24.1	57.6
Weekly wage (£)	493	505	130	254	390	606	911	2,080
Weekly incentive pay (£)	9.3	66.3	0	0	0	0	0.6	220.9
Weekly overtime pay (£)	19	60	0	0	0	0	60.8	280.5
Annual wage (£)	26,024	57,481	4,197	10,937	19,231	30,671	47,000	132,000
Basic paid hours	34.4	10.3	18	34.9	37.5	39.8	42	54.8
Paid overtime hours	1.5	6	0	0	0	0	5.3	20.5
Tenure in years	6.8	7.7	1	1	4	9	17	35
Age	38.9	12	23	29	38	48	56	63

Notes: This table presents some moments (mean, standard deviation and different percentile thresholds) for a set of key variables. Tenure is the number of year an individual has been working in its current firm.

Fig. A.3: Distribution of workers by skill and R&D of firm



Notes: This figure shows the distribution of workers by skill and by R&D intensity. R&D intensity is defined as the log of total R&D expenditure per worker. Skill groups are defined in Appendix A.1.2.3. Distributions are computed on our final sample of private firms above 400 employees.

Table A.9: Share of workers at each skill category and quantiles of R&D

Quantile of R&D	Skill category						Obs.
	Low		Intermediate		High		
	1	2	3	4	5	6	
0 (no R&D)	63.5	5.6	11.7	3.8	15.0	0.3	432,029
1	65.8	7.4	10.2	2.8	13.5	0.2	20,654
2	63.2	8.1	10.2	3.2	14.7	0.5	11,962
3	56.0	9.6	11.2	4.2	18.4	0.6	8,271
4	55.7	6.1	14.8	3.6	19.2	0.7	6,884
5	60.9	4.6	14.2	3.3	16.7	0.4	8,382
6	54.0	6.0	15.0	4.2	19.9	0.9	4,855
7	51.9	9.0	12.2	5.0	21.4	0.6	5,895
8	48.6	8.3	14.4	5.2	22.7	0.7	5,012
9	51.4	8.4	11.6	4.5	23.3	0.7	4,037
10	43.5	9.3	12.7	5.1	28.6	0.8	5,176
11	36.3	10.4	15.6	5.8	31.2	0.7	5,265
12	35.8	9.2	15.6	6.2	32.2	1.0	5,993
13	36.0	7.5	15.1	5.7	35.0	0.8	4,583
14	30.2	9.7	12.9	6.7	39.3	1.0	4,415
15	30.8	8.3	18.9	8.7	31.8	1.4	4,816
16	23.2	7.5	19.9	10.4	37.7	1.3	7,453
17	22.1	6.2	21.0	12.3	37.5	0.9	8,600
18	25.1	7.8	18.7	9.3	37.1	2.0	7,245
19	22.9	13.1	15.6	6.2	39.5	2.8	8,468
20	19.2	6.1	14.5	6.6	41.5	12.2	7,007

Notes: This table presents the average proportion of each skill group by quantile of R&D intensity. Skill groups are defined in Appendix A.1.2.3. Quantiles are the same as in Table A.1.

tions. Although the O*NET data is only based on US workers, we believe that the job descriptions are very similar to those of the UK. To match the different occupation classification we match O*NET data to UK data via isco08.

A.2 Decomposition of variance

We decompose the variance as presented in [Song et al. \(2015\)](#) among others. More specifically, let $w_{i,f}$ be a measure of the log of income of the individual i (we drop time dependence but in practice, all this is computed for one given year) working in firm f . Let \bar{w}_f be the average wage within this firm and \bar{w}_A be the average value of $w_{i,f}$ across all N observations. We have:

$$[w_{i,f} - \bar{w}_A] = [\bar{w}_f - \bar{w}_A] + [w_{i,f} - \bar{w}_f].$$

We take this equality to square and sum over all N individual. By construction, the covariance quantity is equal to 0 and this yields:

$$\text{Var}(w_{i,f}) = \underbrace{\sum_{f=1}^F \frac{N_f}{N} [\bar{w}_f - \bar{w}_A]^2}_{\text{Within-firm variance}} + \underbrace{\sum_{f=1}^F \frac{N_f}{N} \text{Var}(w_{i,f} | f)}_{\text{Between-firm variance}}$$

A.3 Extending the model

Extension to more skilled and unskilled workers

We now consider the more general case with $n \geq 1$ low-occupation workers and $m \geq 1$ high-occupation workers. To determine the equilibrium wages resulting from ex post negotiation, we rely on [Stole and Zwiebel \(1996\)](#). In their framework, if the n^{th} low-occupation worker refuses the wage offer w_n^L , then the remaining $n - 1$ low-occupation workers renegotiate a wage w_{n-1}^L . By induction, this provides a generic expression for the two equilibrium wages $w_{n,m}^L(Q, q, \lambda)$ and $w_{n,m}^H(Q, q, \lambda)$ (up to a constant in q, Q and λ):

$$\begin{aligned} w_{n,m}^L(Q, q, \lambda) &= \frac{(q - q_L)\lambda\theta}{n(n+1)} \sum_{i=0}^n iQ^m q^{i-1} - \frac{\theta(1-\lambda)}{2}(q - q_L) \\ w_{n,m}^H(Q, q, \lambda) &= \frac{(Q - Q_L)\lambda\theta}{m(m+1)} \sum_{i=0}^m iq^n Q^{i-1} - \frac{\theta(1-\lambda)}{2}(Q - Q_L), \end{aligned} \tag{A.1}$$

when assuming equal bargaining powers for high- and low-occupation workers. Note that this extension nests the baseline version of the model since taking $n = 1$ and $m = 1$ yields the same results as above.

The case where $n = 1$ and $m = 2$

In this case, we have:

$$\frac{\partial w_{1,2}^L(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(q - q_L)(Q^2 - 1)}{2} \text{ and } \frac{\partial w_{1,2}^H(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(Q - Q_L) \left(\frac{q(1+2Q)}{3} - 1 \right)}{2},$$

and we can show that¹⁰ $\frac{q(1+2Q)}{3} - 1 < Q^2 - 1$, which, combined with the assumption that $(Q - Q_L) < (q - q_L)$, immediately implies that:

$$\frac{\partial w_{1,2}^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w_{1,2}^H(Q, q, \lambda)}{\partial \lambda}.$$

The case where $n = 2$ and $m = 1$

In this case, we have:

$$\frac{\partial w_{2,1}^L(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(q - q_L)(Q + 2qQ)}{6} - \frac{q - q_L}{2} \text{ and } \frac{\partial w_{2,1}^H(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(Q - Q_L)(q - 1)}{2},$$

Then a sufficient condition for $\frac{\partial w_{2,1}^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w_{2,1}^H(Q, q, \lambda)}{\partial \lambda}$ is that $Q + 2qQ > 3q$ which in turn is always true since $Q > q > 1$.

The case where $n = m$

For a given $n \geq 2$, a sufficient condition for $\frac{\partial w_{n,n}^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w_{n,n}^H(Q, q, \lambda)}{\partial \lambda}$ is:

$$\frac{1}{n(n+1)} \sum_{i=0}^n iQ^n q^{i-1} > \frac{1}{n(n+1)} \sum_{i=0}^n iq^n Q^{i-1},$$

which is equivalent to:

$$\sum_{i=0}^n \frac{i}{q^{n-i+1}} > \sum_{i=0}^n \frac{i}{Q^{n-i+1}},$$

which is automatically true as long as $n \geq 2$.

¹⁰This is straightforward since $Q > q$ implies that: $q(1 + 2Q) < Q(1 + 2Q) < Q(Q + 2Q)$ (recall $Q > 1$).

The case where $n < m$

By induction, for a given $n > 2$, if we assume that $\frac{\partial w_{n,m}^L(Q,q,\lambda)}{\partial \lambda} > \frac{\partial w_{n,m}^H(Q,q,\lambda)}{\partial \lambda}$, then it is easy to show that:

$$\frac{1}{n(n+1)} \sum_{i=0}^n iQ^{m+1}q^{i-1} > \frac{1}{(m+1)(m+2)} \sum_{i=0}^{m+1} iq^nQ^{i-1},$$

and therefore that

$$\frac{\partial w_{n,m}^L(Q,q,\lambda)}{\partial \lambda} > \frac{\partial w_{n,m+1}^H(Q,q,\lambda)}{\partial \lambda}.$$

This case is all the more important since we know that most innovative firms have more high-occupation workers than low-occupation workers.

Finally, note that the case $n < m$ corresponds to more R&D intensive firms as we document in the empirical part of the chapter.

A.4 Additional specifications

A.4.1 Different measures of income

In our baseline results, we have chosen to use the average total labor income received per week during the time of the survey divided by the average total number of hours worked. As explained in subsection [A.1.2.2](#), the numerator includes a fixed salary and additional variable incomes (incentive, overtime and other pay). In this section, we test the sensitivity to our main result to using other measures of income. Results are presented in [Table A.10](#) when the usual set of control variables are included and individual and year fixed effects are added. Column 1 uses the baseline measure (logarithm of total earning per hours) as a reference. Column 2 uses the same measure but restricting to fixed salary and excluding overtime. Column 3 uses the total weekly earnings and column 4 and 5 use total annual earnings including (resp. excluding) bonuses. One concern with our results is that high occupation workers receive most of their income from incentive paid at the end of the year and hence not well captured by our baseline measure of income (based on a standard week in April). This could potentially drive our result if in turns, high occupation workers receive a larger share of their income as incentive in innovative firms. In fact, the average share of bonus in yearly income is 8.8% for non R&D firms against 6.5% for non R&D firms. Finally, comparing column 4 and 5 of [Table A.10](#) shows no substantial differences when bonus are included or excluded.

A.4.2 Different functions of R&D

In this section we show that our main results hold using alternative function of R&D. We consider: $\frac{R\&D}{L}$, $\ln(1 + \frac{R\&D}{L})$, Hyperbolic with R&D, Hyperbolic with $\frac{R\&D}{L}$, $\ln(1 + R\&D)$, $R\&D > 0$ and $R\&D > 0$. Results are shown in [Table A.11](#).

Next, we allow the coefficient to adjust at different point in the R&D distribution. To do so,

Table A.10: Robustness to using different measures of income.

Dependent variable: $\ln(w_{ijkft})$				
Income	Total hourly pay (1)	Fixed hourly pay (2)	Total pay (3)	Fixed pay (4)
$\ln(R_{ft} + 1)$	0.006*** (0.000)	0.005*** (0.000)	0.008*** (0.000)	0.012*** (0.001)
Age^2	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Tenure	0.008*** (0.000)	0.007*** (0.000)	0.006*** (0.000)	0.069*** (0.001)
$Tenure^2$	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.002*** (0.000)
Firm Size	-0.007*** (0.001)	-0.010*** (0.001)	-0.016*** (0.001)	-0.026*** (0.002)
Full-Time	-0.001 (0.002)	0.013*** (0.002)	0.659*** (0.004)	0.495*** (0.006)
Fixed Effects	i+t	i+t	i+t	i+t
R ²	0.888	0.907	0.888	0.800
N	572,786	572,573	575,859	571,052

Notes: This table presents results from estimating equation 2.1 using different measures of income. Column 1 uses the logarithm of total hourly earnings, column 2 uses the logarithm of the basic (fixed) hourly income, column 3 uses the logarithm of the total weekly earning and column 4 uses the logarithm of annual gross earnings. Control variables definition and construction are given in Table A.7. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are computed to indicate the level of significance: ***, ** and * for 0.01, 0.05 and 0.1 levels of significance.

Table A.11: Testing different function of R&D

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\frac{R\&D}{L}$	0.00415***	0.00216***	0.000455***	0.000170*
$\ln(1 + \frac{R\&D}{L})$	0.117***	0.0649***	0.0286***	0.0101***
Hyperbolic with R&D	0.0198***	0.0105***	0.00400***	0.000963***
Hyperbolic with $\frac{R\&D}{L}$	0.0979***	0.0541***	0.0238***	0.00819***
$\ln(1 + R\&D)$	0.0215***	0.0114***	0.00438***	0.00111***
$R\&D > 0$	0.147***	0.0751***	0.0265***	0.00224
$R\&D$	0.282***	0.120***	0.0531***	0.0154**
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
Observations	572,799	572,799	572,799	572,799

Notes: This table presents the coefficient on the function of R&D intensity when estimating equation 2.1 but replacing the log of R&D by alternative functions. The set of control variables and fixed-effects are the same as in Table 2.3. Each line corresponds to a different functional form. Hyperbolic function is $H(x) = \ln(x + \sqrt{x^2 + 1})$. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are computed to indicate the level of significance: ***, ** and * for 0.01, 0.05 and 0.1 levels of significance.

we include a binary variable for each of the twenty quantile of R&D:

$$\ln(w_{ijkft}) = x'_{ift}\beta_1 + z'_{ft}\beta_2 + \sum_{l=1}^{20} \beta_{3l}R_{ftl} + \nu_w + \epsilon_{it} \quad (\text{A.2})$$

Where R_{ftl} is equal to 1 if firm f belongs to quantile l in year t . The resulting estimated coefficients β_{3l} on each of these binary variables are presented in Table A.12. We see that the coefficients are positive and increase with the quantile of R&D for almost all quantiles except for the first ones. The only exception occurs when we use firm fixed effects (column 4) where the coefficients become positive only for the very high quantiles.

A.4.3 Other measures of innovation

In this section, we run our baseline regression using different proxies for the intensity of R&D. As seen in Table A.13, the effect of the intensity of R&D is always positive and significant.

A.4.4 Other robustness

In this last section we test three additional robustness checks. First, as seen in Table A.1, firms from the highest quantile of R&D are very different from others. We thus check that our results are not mainly driven by these firms by removing observations associated with total R&D expenditures higher than 293,634,000 pounds. Results are shown in Table A.14. Second, we run our main regressions restricting on firms with positive expenditures in R&D in the current year. We change the measure of R&D to $\ln(R_{ft})$ with R_{ft} being the total expenditures in R&D of firm f during year t . Results are presented in Table A.15. Third, we test the robustness of our results regarding the different effects of R&D to income by skill to using an alternative definition of skill level as defined in subsection A.1.2.3. Results are robust in the sense that there is no effect of R&D expenditures on income for high occupation workers as

Table A.12: 20 quantiles of R&D based on level of total R&D expenditures

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
Quantile 1	-0.0233***	-0.0172***	-0.00557	-0.0196***
Quantile 2	0.0471***	0.00118	0.0150***	-0.00454
Quantile 3	-0.0170**	-0.0267***	0.00512	0.000841
Quantile 4	-0.0226***	-0.00101	0.0153***	-0.00538
Quantile 5	0.0502***	0.0376***	0.0187***	-0.00229
Quantile 6	0.0267***	0.00483	0.0109***	0.00622
Quantile 7	0.00729	0.0101	0.00132	-0.0362***
Quantile 8	0.0478***	0.0341***	0.00461	-0.0290***
Quantile 9	0.0531***	0.0356***	0.0228***	-0.0137**
Quantile 10	0.0733***	0.0522***	0.0281***	-0.000501
Quantile 11	0.0904***	0.0513***	0.0161***	-0.0181***
Quantile 12	0.0439***	0.0341***	0.0337***	0.00846
Quantile 13	0.0704***	0.0398***	0.0270***	-0.0190***
Quantile 14	0.0745***	0.0483***	0.0269***	0.0168***
Quantile 15	0.146***	0.0961***	0.0330***	0.00276
Quantile 16	0.167***	0.0997***	0.0366***	0.0192***
Quantile 17	0.234***	0.109***	0.0440***	0.0241***
Quantile 18	0.271***	0.141***	0.0492***	0.0249***
Quantile 19	0.248***	0.149***	0.0607***	0.0500***
Quantile 20	0.380***	0.197***	0.0844***	0.0208**
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
Observations	572,799	572,799	572,799	572,799

Notes: This table presents the coefficient on each of the 20 quantiles of total R&D expenditure when estimating equation A.2. The set of control variables and fixed-effects are the same as in Table 2.3. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are computed to indicate the level of significance: ***, ** and * for 0.01, 0.05 and 0.1 levels of significance.

Table A.13: Robustness to using different measures of R&D.

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
R&D	0.0286*** (0.002)	0.0300*** (0.002)	0.0123*** (0.003)	0.239*** (0.024)
Age^2	-0.000590*** (0.000)	-0.000590*** (0.000)	-0.000593*** (0.000)	-0.000592*** (0.000)
Tenure	0.00777*** (0.000)	0.00777*** (0.000)	0.00787*** (0.000)	0.00787*** (0.000)
$Tenure^2$	-0.0000870*** (0.000)	-0.0000867*** (0.000)	-0.0000872*** (0.000)	-0.0000885*** (0.000)
$\ln(emp)$	-0.00721*** (0.001)	-0.00722*** (0.001)	-0.00739*** (0.001)	-0.00712*** (0.001)
Full Time	-0.000678 (0.002)	-0.000666 (0.002)	0.000379 (0.002)	0.000118 (0.002)
Fixed Effects	i+t	i+t	i+t	i+t
N	572,799	572,799	572,799	572,799
R^2	0.888	0.888	0.888	0.888

Notes: This table presents results from estimating the effect of R&D intensity on income. Column 1 uses total R&D expenditures per number of employees, column 2 and 3 uses respectively intramural and extramural R&D expenditures per number of employees and column 4 uses the share of workers involved in R&D activities. All these measures are transformed with a function $\ln(1+x)$. Control variables definition and construction are given in Table A.7. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are computed to indicate the level of significance: ***, ** and * for 0.01, 0.05 and 0.1 levels of significance.

presented in Table [A.16](#) where each column corresponds to a different skill level (1 for the lowest and 4 for the highest).

Table A.14: Robustness: Removing firms from the highest quantile of R&D expenditures.

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\ln(R_{ft} + 1)$	0.123*** (0.003)	0.0694*** (0.002)	0.0295*** (0.002)	0.0143*** (0.003)
Age	0.0584*** (0.001)	0.0340*** (0.000)		0.0446*** (0.001)
Age ²	-0.000703*** (0.000)	-0.000393*** (0.000)	-0.000579*** (0.000)	-0.000523*** (0.000)
Tenure	0.0235*** (0.000)	0.0152*** (0.000)	0.00792*** (0.000)	0.0160*** (0.000)
Tenure ²	-0.000316*** (0.000)	-0.000224*** (0.000)	-0.0000933*** (0.000)	-0.000232*** (0.000)
$\ln(emp)$	-0.0315*** (0.001)	-0.00829*** (0.001)	-0.00743*** (0.001)	-0.0237*** (0.003)
Male	0.162*** (0.003)	0.145*** (0.002)		0.159*** (0.003)
Full Time	0.250*** (0.002)	0.0740*** (0.002)	0.000981 (0.002)	0.143*** (0.002)
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
N	546,556	546,556	546,556	546,556
R ²	0.368	0.614	0.884	0.550

Notes: This table presents estimates of the effect of R&D as measured by the logarithm of 1 + total R&D expenditures divided by employment in the year, on the logarithm of income as measured by the gross hourly earnings (in log). Firm with R&D expenditures higher than 293,634,000 pounds in the current year are excluded (top vintile). Control variables definition and construction are given in Table A.7. Column 1 uses labor market interacted with year fixed effect, column 2 uses labor market interacted with year and occupation fixed effects, column 3 uses firm fixed effects and column 4 uses individual fixed effects. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A.15: Robustness: Removing firms with no R&D expenditures.

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\ln(1 + R_{ft})$	0.0504*** (0.001)	0.0319*** (0.001)	0.00532*** (0.001)	0.00164 (0.001)
Age	0.0650*** (0.001)	0.0407*** (0.001)	0 (.)	0.0560*** (0.001)
Age ²	-0.000745*** (0.000)	-0.000450*** (0.000)	-0.000546*** (0.000)	-0.000635*** (0.000)
Tenure	0.0139*** (0.001)	0.0108*** (0.001)	0.00528*** (0.001)	0.0122*** (0.001)
Tenure ²	-0.000198*** (0.000)	-0.000184*** (0.000)	-0.0000765*** (0.000)	-0.000186*** (0.000)
$\ln(emp)$	-0.0137*** (0.002)	-0.0101*** (0.001)	-0.00132 (0.003)	-0.0326*** (0.006)
Male	0.177*** (0.005)	0.161*** (0.005)	0 (.)	0.166*** (0.005)
Full Time	0.200*** (0.006)	0.0318*** (0.005)	-0.0860*** (0.008)	0.137*** (0.006)
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
N	144,205	144,205	144,205	144,205
R ²	0.407	0.631	0.917	0.512

Notes: This table presents estimates of the effect of R&D as measured by the logarithm of total R&D expenditures divided by employment in the year, on the logarithm of income as measured by the gross hourly earnings (in log). Firm with 0 R&D expenditures are excluded. Control variables definition and construction are given in Table A.7. Column 1 uses labor market interacted with year fixed effect, column 2 uses labor market interacted with year and occupation fixed effects, column 3 uses firm fixed effects and column 4 uses individual fixed effects. Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A.16: Robustness: Alternative measure of skill.

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\ln(R_{ft} + 1)$	0.0359*** (0.007)	0.0339*** (0.003)	0.00985*** (0.003)	-0.00117 (0.002)
Age^2	-0.000208*** (0.000)	-0.000361*** (0.000)	-0.000613*** (0.000)	-0.000875*** (0.000)
Tenure	0.00733*** (0.001)	0.00932*** (0.001)	0.00342*** (0.001)	0.00144** (0.001)
$Tenure^2$	-0.000124*** (0.000)	-0.000151*** (0.000)	-0.0000538*** (0.000)	-0.00000546 (0.000)
$\ln(emp)$	0.00360* (0.002)	-0.00645*** (0.001)	0.000285 (0.003)	0.00625** (0.003)
Full Time	-0.0428*** (0.006)	-0.0159*** (0.003)	-0.120*** (0.011)	-0.118*** (0.013)
Skill Level	1 (low)	2	3	4 (high)
Fixed Effects	i+t	i+t	i+t	i+t
N	92,305	268,760	104,647	107,087
R^2	0.701	0.784	0.870	0.900

Notes: This table presents estimates of the effect of R&D as measured by the logarithm of 1 + total R&D expenditures divided by employment in the year, on the logarithm of income as measured by the gross hourly earnings (in log). Control variables definition and construction are given in Table A.7. Column 1 restricts to lowest skill workers (skill level 1) with the alternative definition of skill presented in subsection A.1.2.3. Column 2 restricts to skill level 2, etc... Ordinary Least Square regression. Heteroskedasticity robust standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

APPENDIX B

Appendix of Chapter 2

B.1 Data description

B.1.1 Patent data

Our first database is PATSTAT Spring 2015 which contains detailed information about patent applications from every patent office in the world. Each patent can be exactly dated to the day of application, which is sometimes referred to as the “filling date”. Moreover, we can retrieve all the future patents making citations to the patents up to 2014.

Counting patent applications Each French firm is associated with a number of patent applications by that firm each year (how this match is done is explained in [Lequien et al., in progress](#)). If the firm shares a patent with another firm, then we only allocate a corresponding share of this patent to the firm. We restrict attention to patents that have been granted by 2015. This raises the well-documented issue of truncation bias [Hall et al. \(2005\)](#). Indeed as we come closer to the end of the sample, we observe a smaller fraction of all patents since many of them are not yet granted ¹ In addition, there is a legal obligation to wait 18 months before publication in PATSTAT. With our version of Spring 2016 this implies that we can assume the data to be reasonably complete up to 2012. To avoid this issue, an alternative solution

¹The time between patent application and patent granting is a little more than 2 years on average but the distribution of this lag is very skewed with few patent applications still waiting for patent granting many years after the application.

could be to use the year of granting instead of the year of application. However, the former is less relevant than the latter as it is affected by administrative concerns and also by potential lobbying activities that have little to do with the innovation itself. In order to be as close to the time of the innovation as possible, we follow the literature and consider the filing date. We count every patent owned by a French firm, regardless of the patent office that granted the patent rights. Here we need to be aware of the differences in regulations across intellectual property offices. Some patent offices, especially those of Japan and Korea, offer less breadth to a patent, which implies that more patents are needed to protect a given invention than in other patent offices (see [de Rassenfosse et al., 2013](#)). Since we only consider French firms, this would become an issue only if some French firms patent a lot in countries like Japan or Korea, in which case the number of patents by such firms would be artificially large. To check that this problem does not drive our results, we build three different measures of patent counts as a robustness test: (i) we count only priority patents which correspond to the earliest patents which relate to the same invention; (ii) we count the number of patent families: patents are indeed classified into the same patent family when they protect the same invention, even if these patents get granted by different patent offices; (iii) we count the number of triadic families, that is, families containing patents from the largest three intellectual property offices: Japan (JPO), the US (USPTO) and Europe (EPO). We also look at how our results are affected when Japan is being replaced by China, given the recent rise in Chinese patents.

B.1.2 Firm-level accounting data

Our second data source provides us with accounting data for French firms from the DGFIP-INSEE, this data source is called FICUS and FARE. The corresponding data are drawn from compulsory reporting of firms and income statements to fiscal authorities in France. Since every firm needs to report every year to the tax authorities, the coverage of the data is all

French firms from 1994 to 2012 with no limiting threshold in terms of firm size or sales. This dataset provides us with information on the turnover, employment, value-added, the four-digit sector the firm belongs to . . . This corresponds to around 47 million observations and the number of observations per year increases from 1.9m to 3.9m over the period we consider.

The manufacturing sector is defined as category C of the first level of the NAF (*Nomenclature d'Activités Française*), the first two digits of which are common to both NACE (Statistical Classification of Economic Activities in the European Community) and ISIC (International Standard Industrial Classification of All Economic Activities). Insee provides each firm with a detailed principal activity code (APE) with a top-down approach: it identifies the 1-digit section with the largest value added. Among this section, it identifies the 2-digit division with the largest value-added share, and so on until the most detailed 5-digit APE code ([INSEE \(2016\)](#)). It is therefore possible that another 5-digit code shows a larger value-added share than the APE identified, but one can be sure that the manufacturing firms identified produce a larger value-added in the manufacturing section than in any other 1-digit section, which is precisely what we rely on to select the sample of most of our regressions. The 2-digit NAF sector, which we rely intensively on for our fixed effects, then represents the most important activity among the main section of the firm. Employment each year is measured on average within the year and may therefore be a non-integer number. The age of the firm has been retrieved from the reported date of creation.

A unique 9-digit identifier called *Siren number* is associated to each firm, this number is given to the firm until it disappears and cannot be assigned to another firm in the future. When a firm merges with another firm, or is acquired by another firm, or makes significant changes in its organization, this number may change over time. Hence, new entrant *Sirens* in our database do not necessary correspond to new firms.

B.1.3 Trade data

Customs data for French firms Detailed data on French exports by product and country of destination for each French firm are provided by the French Customs. These are the same data as in [Mayer et al. \(2014\)](#) but extended to the whole 1994-2012 period. Every firm must report its exports by destination country and by very detailed product (at a level finer than HS6). However administrative simplifications for intra-EU trade have been implemented since the Single Market, so that when a firm annually exports inside the EU less than a given threshold, these intra-EU flows are not reported and therefore not in our dataset. The threshold stood at 250 000 francs in 1993, and has been periodically reevaluated (650 000 francs in 2001, 100 000 euros in 2002, 150 000 euros in 2006, 460 000 euros in 2011). Furthermore flows outside the EU both lower than 1 000 euros in value and 1 000 kg in weight are also excluded until 2009, but this exclusion was deleted in 2010.

B.1.4 Matching

Our paper is the first to merge those three very large -patent, administrative, and custom-datasets covering exporting French firms. Merging administrative firm-level data from FICUS/FARE and Customs data is fairly straightforward² as a firm can be identified by its *Siren* identifier in both datasets. Thus the main challenge is to match either of these two datasets with PATSTAT. Indeed, PATSTAT only reports the name of the patent owner. Not only can this name be slightly different from the name reported in the other two databases, but it may also change over time, for example because of spelling mistakes. We thus relied on the work of [Lequien et al. \(in progress\)](#) who developed a matching algorithm to map patents with the corresponding French firms. The match is not perfect for reasons that are detailed in their paper, but most of the patents associated to private firms have been successfully merged.

²Although one must keep track of the different definitions of firms across these two datasets.

Lequien et al. (in progress) proceed in three main steps to merge PATSTAT and SIRENE:

1. For each *Siren* number from SIRENE, find a small subset of applicant firms in Patstat with phonetic similarities:
 - perform cleaning, splitting and phonetic encoding on firms' name in both databases. Too common words are deleted (THE, AND, CO, FRANCAISE ...).
 - sort each name by least frequent encoding in SIRENE. The more often a word appears in the database, the less information it can convey to identify firms.
 - for each SIRENE firm, the first (ie least frequent) cleaned word of the firm's name is compared with every PATSTAT name. All the PATSTAT names containing this word form a first subset of possible matches. Then the second word of the firm's name is compared with every name in this subset, reducing it further. This procedure stops before arriving at a null subset, and yields a set of likely PATSTAT matches for each SIRENE name. Very often this set is null because the majority of firms do not patent. On average, this subset contains 10 applicants, reducing a lot the computationally intensive comparisons.
2. Computation of parameters on these possible matches
 - Comparison of the names (raw names, and cleaned names), using Levenshtein distances and an inclusion parameter (all the words in one name are included in the name from the other database)
 - zip code comparison (*code postal*)
 - date comparisons (a firm cannot have patented before its creation)
3. Matching with supervised learning

- Sample from INPI (*Institut National de la Propriété Intellectuelle*) with 15,000 true matches between *Siren* number and PATSTAT *person id* (and in total 170,000 pairs, with the corresponding known mismatches).
- This sample is randomly split into a learning sample and a verification sample (this procedure is repeated 10 times, and the recall and precision measures are averaged over them, so that the choice of the sample does not alter the results). This allows to choose the relevant variables and estimate the parameters.
- apply this model on all the possible matches identified in the previous step.
- in 90% of cases, unique matching. In the remaining 10% of cases, filter further with a decision tree (is the date of creation of the firm lower than the first filing of the applicant?, which couple has the minimum Levenshtein distance between raw names, between cleaned names, is one of the names included in the other?, which firm has the maximum number of employees?)

The recall rate (share of all the true matchings that are accurate) is at 86.1% and the precision rate (share of the identified matches that are accurate) is at 97.0%.

B.1.5 Other data

Two other datasets are used to construct the trade demand variables. CEPII's database BACI, based on the UN database COMTRADE, provides bilateral trade flows in value and quantity for each pair of countries from 1995 to 2015 at the HS6 product level, which covers more than 5,000 products. IMF's *World Economic Outlook* provides country information such as GDP or GDP per capita in ppp.

B.2 Additional tables

Table B.1: Exporters and innovators are bigger

	Non-exporters		Exporters		Total
	Non-innovator	Innovator	Non-innovator	Innovator	
Firms	689,267	1,978	130,104	9,365	830,714
Employment	21	41	53	256	40
Sales	2,102	6,432	13,725	78,748	7,490
Value Added	753	2,106	2,839	20,115	1,965
Age	11	13	19	21	13
Exports	0	0	1,067	16,362	763
Countries	0	0	3	13	1
Patents	0	0.5	0	2.4	0.1

Notes: This table presents basic descriptive statistics across four categories of all firms whether they innovate, export, both or none. Employment is given in full-time equivalent on average over the year and exports, sales and value added are in thousand of euros. Countries is the number of destination countries for exports. Employment, Sales, Value Added, Age, Exports, Countries and Patents are taken as a yearly average over the whole period 1995-2012.

Table B.2: Different trimming

Dependent variable	Number of patents					
	D_{ft}^{Ms} 2.5% (baseline) (1)	D_{ft}^{Ms} 0% (2)	D_{ft}^{Ms} 1% (3)	D_{ft}^{Ms} 2% (4)	D_{ft}^{Ms} 3% (5)	D_{ft}^{Ms} 5% (6)
Demand	-3.269** (1.014)	-0.752** (0.305)	-2.000*** (0.745)	-3.060*** (0.925)	-3.501*** (1.119)	-3.490*** (1.256)
Decile \times Demand	0.962*** (0.255)	0.166** (0.082)	0.511*** (0.169)	0.843*** (0.227)	1.067*** (0.285)	1.089*** (0.327)
Nb of observation	77,901	82,043	80,378	78,722	77,077	73,784
R ²	0.905	0.890	0.901	0.905	0.907	0.916

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Different trimming on extreme variations of the Demand variable are done. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.3: Removing first years

Dependent variable	Number of patents			Number of triadic patents		
	D_{ft}^{Ms}	D_{ft}^{Ms}	D_{ft}^{Ms}	D_{ft}^{Ms}	D_{ft}^{Ms}	D_{ft}^{Ms}
Years removed	$t < t_0 + 2$	$t < t_0 + 3$	$t < t_0 + 5$	$t < t_0 + 2$	$t < t_0 + 3$	$t < t_0 + 5$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-2.712*** (1.003)	-2.382*** (0.938)	-1.440 (0.966)	-0.796*** (0.274)	-0.733*** (0.276)	-0.657** (0.329)
Decile \times Demand	0.813*** (0.249)	0.655*** (0.229)	0.362* (0.215)	0.192*** (0.059)	0.147** (0.059)	0.102 (0.140)
Nb of observation	72,265	66,684	55,880	72,265	66,684	55,880
R ²	0.919	0.927	0.941	0.912	0.920	0.934

Notes: This table presents regression results of an OLS estimation of equation 3.7. First years following t_0 are excluded from the estimation. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.4: Baseline results - Clustered standard errors

Dependent variable	Number of patents			Number of triadic patents		
	D_{ft}^{Ms}	D_{ft}^{MI}	D_{ft}^G	D_{ft}^{Ms}	D_{ft}^{MI}	D_{ft}^G
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-3.269** (1.475)	-2.585* (1.530)	-3.037 (2.089)	-0.868** (0.352)	-0.816 (0.521)	-0.851 (0.629)
Decile \times Demand	0.962*** (0.372)	0.911** (0.444)	0.852 (0.552)	0.222*** (0.078)	0.176 (0.119)	0.304** (0.253)
Nb of observation	77,901	77,918	77,002	77,901	77,918	77,002
R ²	0.905	0.897	0.901	0.895	0.889	0.884

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Heteroskedasticity robust standard errors clustered at the firm level ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.5: Control for firm size - Triadic applications

Dependent variable	Number of triadic patents					
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_s}$ (6)
Demand	-0.868*** (0.265)	-0.893*** (0.271)	-0.849*** (0.267)	-0.843*** (0.265)	-0.738*** (0.254)	-0.866*** (0.263)
Decile \times Demand	0.222*** (0.060)	0.224*** (0.062)	0.219*** (0.060)	0.221*** (0.060)	0.199*** (0.061)	0.226*** (0.060)
Size		0.166*** (0.038)	0.186*** (0.036)	0.324*** (0.071)	0.535*** (0.109)	0.315*** (0.063)
Nb of observation	77,901	76,236	76,678	76,860	77,240	77,605
R ²	0.895	0.896	0.896	0.896	0.895	0.896

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.6: Control for productivity specific trend (2)

Dependent variable	Number of patents			Number of triadic patents		
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_I}$ (2)	D_{ft}^G (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_I}$ (5)	D_{ft}^G (6)
Demand	-2.728*** (1.021)	-2.272** (1.158)	-0.726 (1.678)	-0.686* (0.371)	-0.854* (0.457)	-0.148 (0.609)
Decile \times Demand	0.857*** (0.274)	0.869*** (0.336)	0.369 (0.472)	0.233** (0.098)	0.312** (0.125)	0.462*** (0.165)
Nb of observation	77,901	77,918	77,002	77,901	77,918	77,002
R ²	0.906	0.897	0.901	0.854	0.854	0.850

Notes: This table presents regression results of an OLS estimation of equation 3.7 to which a productivity decile specific time trend is added. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.7: Alternative definition of frontier - Triadic patent applications

Dependent variable	Number of triadic patents					
	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_s}$ (6)
Demand	-0.868*** (0.265)	-0.385 (0.237)	-1.790*** (0.383)	-0.034 (0.260)	0.173 (0.256)	0.143 (0.245)
Interaction	0.222*** (0.060)	0.127* (0.065)	1.281*** (0.320)	0.942** (0.459)	0.688 (0.609)	1.910* (1.117)
Nb of observation	77,901	77,901	77,901	77,901	77,901	77,901
R ²	0.895	0.895	0.895	0.895	0.895	0.895

Notes: This table presents regression results of an OLS estimation of equation 3.7. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Variable interaction is defined as the product of our demand variable and a variable capturing the frontierness of the firm. Column 1 is our baseline model, column 2 uses productivity deciles using sales over employment instead of value added over employment, columns 3 to 6 no longer construct decile groups but use a dummy variable for being above the 50th, 75th, 90th and 95th percentile of the initial productivity distribution. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.8: Other Dependent Variables - First Difference (2)

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.018 (0.016)	-0.019 (0.020)	-0.008 (0.018)	-0.001 (0.012)	-0.004 (0.010)
Decile \times Demand	0.009*** (0.003)	0.009*** (0.003)	0.005* (0.003)	0.003* (0.002)	0.000 (0.002)
Nb of observation	69,472	69,793	69,731	66,780	69,511
R ²	0.158	0.143	0.121	0.085	0.061
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.005 (0.017)	-0.015 (0.023)	0.006 (0.020)	0.011 (0.018)	0.005 (0.018)
Decile \times Demand	0.008*** (0.003)	0.008** (0.003)	0.004 (0.003)	0.003 (0.003)	0.004 (0.003)
Nb of observation	33,167	33,319	33,291	32,859	33,210
R ²	0.179	0.160	0.134	0.120	0.081

Notes: This table presents regression results of an OLS estimation of a regression of the first difference of various firm specific characteristics on our demand variable and its interaction with a productivity decile. $\tilde{D}_{ft}^{M_s}$ represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.9: Other Dependent Variables - Level (2)

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.225*** (0.052)	0.002 (0.054)	-0.091* (0.051)	-0.038 (0.023)	-0.008 (0.021)
Decile \times Demand	0.045*** (0.008)	0.011 (0.009)	0.024*** (0.008)	0.002 (0.004)	0.005 (0.004)
Nb of observation	75,879	76,176	76,041	71,173	66,212
R ²	0.948	0.946	0.950	0.875	0.885
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.048 (0.059)	0.228*** (0.061)	0.081 (0.058)	0.110*** (0.041)	0.006 (0.038)
Decile \times Demand	0.040*** (0.009)	0.006 (0.009)	0.020*** (0.009)	0.003 (0.007)	0.0178*** (0.006)
Nb of observation	33,167	33,319	33,291	32,859	33,210
R ²	0.179	0.160	0.134	0.120	0.081

Notes: This table presents regression results of an OLS estimation of a regression of the log of the level of various firm specific characteristics on our demand variable and its interaction with a productivity decile. $\tilde{D}_{ft}^{M_s}$ represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.10: Other Dependent Variables - First Difference (2)

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.018 (0.016)	-0.019 (0.020)	-0.008 (0.018)	-0.001 (0.012)	-0.004 (0.010)
Decile \times Demand	0.009*** (0.003)	0.009*** (0.003)	0.005* (0.003)	0.003* (0.002)	0.000 (0.002)
Nb of observation	69,472	69,793	69,731	66,780	69,511
R ²	0.158	0.143	0.121	0.085	0.061
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.005 (0.017)	-0.015 (0.023)	0.006 (0.020)	0.011 (0.018)	0.005 (0.018)
Decile \times Demand	0.008*** (0.003)	0.008** (0.003)	0.004 (0.003)	0.003 (0.003)	0.004 (0.003)
Nb of observation	33,167	33,319	33,291	32,859	33,210
R ²	0.179	0.160	0.134	0.120	0.081

Notes: This table presents regression results of an OLS estimation of a regression of the first difference of various firm specific characteristics on our demand variable and its interaction with a productivity decile. $\tilde{D}_{ft}^{M_s}$ represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B.11: Other Dependent Variables - Level (2)

Panel 1: All firms					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.225*** (0.052)	0.002 (0.054)	-0.091* (0.051)	-0.038 (0.023)	-0.008 (0.021)
Decile \times Demand	0.045*** (0.008)	0.011 (0.009)	0.024*** (0.008)	0.002 (0.004)	0.005 (0.004)
Nb of observation	75,879	76,176	76,041	71,173	66,212
R ²	0.948	0.946	0.950	0.875	0.885
Panel 2: Above median firms in terms of export intensity					
Dependent variable	Employment	Sales	Wage	Exports	Sales from Export
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$\tilde{D}_{ft}^{M_s}$ (4)	$\tilde{D}_{ft}^{M_s}$ (5)
Demand	-0.048 (0.059)	0.228*** (0.061)	0.081 (0.058)	0.110*** (0.041)	0.006 (0.038)
Decile \times Demand	0.040*** (0.009)	0.006 (0.009)	0.020** (0.009)	0.003 (0.007)	0.0178*** (0.006)
Nb of observation	33,167	33,319	33,291	32,859	33,210
R ²	0.179	0.160	0.134	0.120	0.081

Notes: This table presents regression results of an OLS estimation of a regression of the log of the level of various firm specific characteristics on our demand variable and its interaction with a productivity decile. $\tilde{D}_{ft}^{M_s}$ represents our demand variable that is not standardized by the export intensity coefficient. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 3.4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

APPENDIX C

Appendix of Chapter 3

C.1 Data description

C.1.1 Data sources

We use French firm-level data merged with real estate prices at the *département* level.¹

C.1.1.1 firm-level information

We exploit a large French firm-level database constructed by the Bank of France: **FiBEn**. **FiBEn** is based on fiscal documents, including balance sheet and P&L statements, and contains detailed information on flow and stock accounting variables as well as information on firms' activities, location and workforce size.

The database includes French firms with annual sales exceeding 750,000 euros or with outstanding credit exceeding 380,000 euros. It has a large coverage of French medium and large firms. Using a dummy variable indicating if firms operate in more than one establishment, we only retain single establishment firms and we restrict our sample to firms with total headcount below 250 to ensure the validity of this information. We also exclude from our sample firms operating in the retail industry and the hotel and catering industry. Those sectors are indeed

¹There are 94 départements in mainland France, a complete list can be found in Table C.1. Because of the lack of reliable data regarding real estate price, we excluded departments 12 (Aveyron), 46 (Lot) and 53 (Mayenne).

characterized by small catchment areas than can be affected by short-distance relocations.² We keep firms that declare data over at least three consecutive years. Our panel is unbalanced as firms may enter and exit the sample between 1994 and 2013.³

C.1.1.2 Real estate prices

We need real estate prices to compute capital gains on real estate assets as well as real estate volume. Commercial real estate local prices being not available in France, we use residential prices. More precisely, we use the *Notaires-INSEE*⁴ apartment price indices built by [Fougère and Poulhes \(2012\)](#) which are based on the data collected by French *notaires* and the methodology developed by the INSEE.⁵ These indices take into account changes in the quality of apartments since hedonic characteristics of the flats are used to build the indices. The indices in each *département* are standardized to be equal to 100 in 2000. In addition, we have apartment per square meter prices in each *département* in 2013. Apartment per square meter prices at the *département* level are collected by the *Chambre des Notaires*. They correspond to the average price per square meter of all apartment transactions registered in a given year.⁶ We reinterpolate apartment prices using the apartment price index to build apartment prices per square meter at the *département* level from 1994 onwards. Prior to 1994, housing price indices used to reinterpolate the series are taken from [Friggit \(2009\)](#). We use the Paris housing price index (available from 1840 onwards) for *départements* located in the Paris area (*Île-de-France*) and the national housing price index (available from 1936 onwards) for all the other *départements*. We report the evolution of real estate prices given in thousand of 2013 euros in each

²Note that keeping those sectors in the database has no effects on the results

³We cannot conclude that a firm exiting the sample has gone bankrupt as it may have merely crossed the above-mentioned declaration thresholds; alternatively it may have been bought by another firm.

⁴Solicitor is the English equivalent for the French word *notaire*

⁵The National Institute of Statistics and Economic Studies, the French National Statistical Bureau.

⁶The *Chambre des Notaires de Paris* has registered apartment prices in the database *Bien* from 1992 onwards and the *Notaires de France* started to register those prices for the rest of mainland France in the database *Perval* in 1994.

Département in Table C.2.

Real estate prices at the *département* level being less precise before 1994, we start our analysis in 1994. We also restrict our study to the firms headquartered in so-called "*départements de France métropolitaine*" (mainland France), excluding overseas territories and Corsica.

C.1.2 Variable construction and further descriptive statistics

C.1.2.1 Firms mobility

We derive information on firms relocation behaviour thanks to the reported location of headquarters. **FiBEn** provides, at annual frequencies, the municipality where the headquarters are located at the end of the year. We identify the occurrence of a relocation when we observe a change in the municipality of the headquarters. Hence, we only identify relocations across municipalities and clearly underestimate the number of relocations.

Besides, in order to insure that the headquarters' relocation coincides with the relocation of the whole firm's activities, we restrict our analysis to single establishment firms. Single establishment firms account for around 80% of the firms registered in **FiBEn**.

We mentioned in the introduction that a concurrent strategy to local relocation might consist in opening new establishments (branching). We find that 2% of the firms initially identified as single-establishment turn to multi-establishment structures. When compared to the 13.2% of firms relocating locally, this finding shows that local relocation is a much more common event than branching.

For each relocation observed we compute the "as-the-crow-flies" distance between the municipality of departure and the municipality of arrival using the latitude and the longitude of the center of the municipality from the National Geographic Institute (IGN). The distance is below 7.5km for 50% of the relocations; it is below 16km for 75 percent of the relocating firms. We

Table C.1: French *Départements* in 2013

<i>Département</i> name	<i>Département</i> code	Population	<i>Département</i> name	<i>Département</i> code	Population
Ain	01	634 173	Lozère	48	76 204
Aisne	02	538 743	Maine-et-Loire	49	809 505
Allier	03	343 680	Manche	50	500 019
Alpes-de-Haute-Provence	04	162 924	Marne	51	572 968
Hautes-Alpes	05	140 706	Haute-Marne	52	179 638
Alpes-Maritimes	06	1 081 821	Mayenne	53	307 831
Ardèche	07	323 543	Meurthe-et-Moselle	54	729 664
Ardennes	08	278 970	Meuse	55	190 550
Ariège	09	153 011	Morbihan	56	747 458
Aube	10	308 085	Moselle	57	1 047 013
Aude	11	370 056	Nièvre	58	212 111
Aveyron	12	278 062	Nord	59	2 607 174
Bouches-du-Rhône	13	2 007 684	Oise	60	822 858
Calvados	14	693 277	Orne	61	286 256
Cantal	15	146 299	Pas-de-Calais	62	1 466 483
Charente	16	354 586	Puy-de-Dôme	63	646 537
Charente-Maritime	17	639 596	Pyrénées-Atlantiques	64	670 434
Cher	18	311 768	Hautes-Pyrénées	65	228 304
Corrèze	19	238 713	Pyrénées-Orientales	66	472 033
Corse-du-Sud	2A	152 720	Bas-Rhin	67	1 118 009
Haute-Corse	2B	174 178	Haut-Rhin	68	763 716
Côte-d'Or	21	533 023	Rhône	69	1 816 373
Côtes-d'Armor	22	599 438	Haute-Saône	70	238 181
Creuse	23	119 381	Saône-et-Loire	71	555 840
Dordogne	24	418 219	Sarthe	72	572 135
Doubs	25	536 474	Savoie	73	429 253
Drôme	26	501 154	Haute-Savoie	74	791 094
Eure	27	599 518	Paris	75	2 218 536
Eure-et-Loir	28	435 171	Seine-Maritime	76	1 255 587
Finistère	29	907 423	Seine-et-Marne	77	1 391 429
Gard	30	748 509	Yvelines	78	1 424 411
Haute-Garonne	31	1 335 366	Deux-Sèvres	79	372 586
Gers	32	191 639	Somme	80	571 595
Gironde	33	1 542 964	Tarn	81	386 004
Hérault	34	1 123 990	Tarn-et-Garonne	82	255 666
Ille-et-Vilaine	35	1 039 983	Var	83	1 041 681
Indre	36	225 590	Vaucluse	84	554 619
Indre-et-Loire	37	606 164	Vendée	85	667 970
Isère	38	1 253 614	Vienne	86	433 682
Jura	39	259 455	Haute-Vienne	87	375 363
Landes	40	405 213	Vosges	88	371 792
Loir-et-Cher	41	332 775	Yonne	89	340 884
Loire	42	761 357	Territoire de Belfort	90	145 074
Haute-Loire	43	227 509	Essonne	91	1 279 864
Loire-Atlantique	44	1 358 627	Hauts-de-Seine	92	1 603 379
Loiret	45	670 906	Seine-Saint-Denis	93	1 573 959
Lot	46	173 021	Val-de-Marne	94	1 372 018
Lot-et-Garonne	47	334 106	Val-d'Oise	95	1 210 318

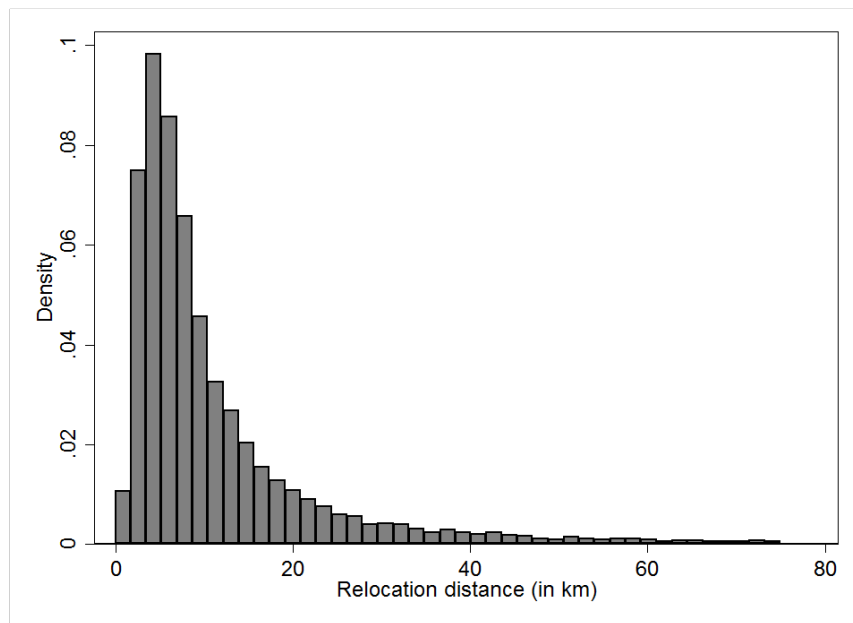
Notes: List of French *département* in 2013 and population. The codes presented in this table are consistent from 1994 to 2013. Source: INSEE.

Table C.2: Real estate prices and propensity to relocation across *départements*

id	(1)	(2)	(3)	(4)	id	(1)	(2)	(3)	(4)	id	(1)	(2)	(3)	(4)
1	1 101	0.76	1.89	1.19%	33	2 032	0.81	2.6	1.78%	66	559	0.91	2	0.97%
2	657	0.83	1.36	0.87%	34	1 212	1.5	2.75	1.52%	67	1 831	1.25	2.15	1.36%
3	399	0.43	1.05	1.13%	35	1 593	1.32	2.28	1.14%	68	1 236	0.59	1.52	1.28%
4	183	0.81	1.87	1.03%	36	305	0.47	1.06	0.75%	69	3 396	1.74	2.77	2.51%
5	217	0.71	2.15	0.77%	37	902	0.97	2.02	1.65%	70	357	0.5	1.03	0.73%
6	1 452	1.96	3.75	1.31%	38	2 230	1.24	2.16	1.45%	71	987	0.73	1.14	0.95%
7	426	0.68	1.4	1.06%	39	541	0.54	1.33	0.69%	72	687	0.66	1.39	1.05%
8	431	0.57	1.13	1.14%	40	473	1.01	2.3	0.79%	73	894	1.36	2.61	1.50%
9	196	0.97	1.72	0.86%	41	513	0.7	1.47	0.70%	74	1 571	1.38	3.26	1.44%
10	532	0.49	1.28	1.20%	42	1 511	0.66	1.14	1.17%	75	4 990	2.89	8.14	3.40%
11	396	0.93	2.11	0.49%	43	401	0.41	1.12	0.82%	76	1 672	0.98	1.93	1.71%
13	2 932	1.07	2.54	1.43%	44	1 738	1.13	2.52	1.32%	77	2 005	1.16	2.69	1.56%
14	888	1.66	2.37	1.59%	45	925	1.05	1.8	1.16%	78	1 746	1.65	3.78	2.12%
15	199	0.52	1.3	0.68%	47	528	0.4	1.15	1.00%	79	591	0.6	1.19	0.90%
16	535	0.42	1.02	1.07%	48	110	0.68	1.49	0.37%	80	672	1.02	2.08	0.86%
17	827	1.7	2.97	0.83%	49	1 400	0.96	1.7	1.10%	81	656	0.81	1.45	0.70%
18	438	0.72	1.26	0.87%	50	637	0.77	1.51	1.09%	82	344	0.51	1.39	0.48%
19	331	0.52	1.18	0.68%	51	1 044	1.15	1.93	0.96%	83	1 123	1.3	3.08	1.34%
21	846	0.97	2	1.45%	52	275	0.7	1.1	0.51%	84	882	0.92	1.91	0.93%
22	905	0.92	1.6	0.93%	54	801	0.73	1.62	1.60%	85	1 240	1.35	2.33	0.68%
23	139	0.47	0.94	0.42%	55	209	0.48	1.13	0.75%	86	640	1.18	1.59	0.98%
24	601	0.64	1.35	1.03%	56	1 020	1.15	2.08	1.01%	87	515	0.71	1.22	0.86%
25	892	0.77	1.64	1.14%	57	1 068	0.8	1.59	1.41%	88	629	0.57	1.11	0.77%
26	1 015	0.63	1.46	1.05%	58	243	0.47	0.95	0.86%	89	486	0.86	1.4	0.96%
27	716	0.9	1.67	1.27%	59	3 185	1.08	2.39	1.79%	90	169	0.67	1.21	1.53%
28	625	1.11	2.01	1.09%	60	1 006	1.45	2.35	1.50%	91	1 819	1.28	2.69	2.30%
29	1 191	0.45	1.37	0.85%	61	404	0.47	1	0.94%	92	2 511	2.27	5.26	3.51%
30	853	0.88	1.92	1.08%	62	1 625	1.25	2.02	1.33%	93	1 943	1.48	3.2	2.71%
31	1 830	1.04	2.39	1.60%	63	954	0.6	1.68	1.18%	94	1 888	1.87	4.19	2.47%
32	261	0.51	1.44	0.25%	64	1 127	0.99	2.36	1.32%	95	1 330	1.17	2.76	2.08%
33	2 032	0.81	2.6	1.78%	65	272	0.62	1.54	1.10%					

Notes: This table presents some descriptive statistics across *départements*. Column 1 gives the number of mono-establishments firms observed across the time period 1994-2013, column 2 gives the level of real estate prices in 1994 in thousands euros of 2010 per square meters, column 3 gives the level of real estate prices in 2013 in thousands euros of 2010 per square meters and column 4 gives the percentage of firms that have relocated, on average, each year over the period 1994-2013. *Départements* names are given in Table C.1. Source: FiBEn, INSEE.

Fig. C.1: Histogram of the distances between the place of departure and the place of settlement



Notes: This Figure plots the distribution of the as-the-crow-flies distances between the place of departure and the place of settlement of a relocating firm. For the sake of readability, we restrict our analysis to relocations characterized by a distance inferior to 50km ; the percentile 90 in the distances distribution is 60km and the percentile 99 is around 600km. Period of observation: 1994-2013. Source: authors calculations based on FiBEEn.

report in Figure C.1 the histogram of the distances between the place of departure and the place of settlement.

C.1.2.2 Real estate assets and capital gains

Real estate assets reported in the balance sheet are not mark-to-market. The market value of firms real estate holdings is important in our analysis because it determines the capital gains on which a tax is levied in the event of a sale.

Nevertheless, firm's balance sheets provide information on gross value of land and buildings and on accumulated amortizations of buildings. The gross value of land and buildings corresponds to their historical value adjusted by accounting reevaluations. A proxy for the mean age of real

estate assets can be recover thanks to the ratio of the accumulated amortizations of buildings over the gross book value of buildings when we assume that buildings are linearly amortized.⁷

We do not have precise information on the location of the firm's real estate assets. Consequently, we use the *département* where the firm is headquartered as a proxy for the location of real estate assets.⁸ In order to recover the market value of real estate units held by the firm, we multiply the historical value of real estate holdings by the accrued changes in the real estate prices in the headquarters's *département* since the average acquisition date. We eventually obtain, for each firm×year observation, the market-value of real estate holdings.

With the market-value, we can compute the capital gains on real estate assets by subtracting the historical value to the market-value. The amount of realized capital gains does not necessarily constitute the fiscal base. Indeed, the tax scheme takes into account the holding period. After a five-year holding period the gains retained in the tax base are diminished by 10% each year; so that after a fifteen-year holding period the firm is not anymore subject to the tax.

For each firm×year observations, we build a variable indicating the share of the proceeds that would paid by the firm under the heading of tax on capital gains in the event of a sale of the real estate assets. This variable varies with:

- (i) The marginal tax rate: constant across firms and equal to the corporate tax rate as capital gains are added to the net income of the firm.
- (ii) The dynamics of real estate prices since the acquisition date: varying with the *département*.
- (iii) The length of time since acquisition: varying with the acquisition date and the year in which the firm is observed.

⁷The accounting standard for the length of the amortization period depends on the nature of the buildings. We retain an average length of 25 years following Chaney et al. (2013).

⁸As we restrict our analysis to single-establishment firms, this is a mild assumption.

Table C.3: Variables description

Variable	Description
Employment	Full-time equivalent (FTE) number of workers as reported by the firm.
Real Estate Owner	Dummy variable equal to one if the firm reports real estate assets in its balance-sheet.
Relocation	Number of local relocations over the observed period divided by the size of this period.
Age	Number of years since company's incorporation.
Size	Net value of the assets reported in the balance sheet in constant million of euros of 2010.
Age of Real Estate	Average age, in years, of real estate assets held by the firm.
Tax	Share, in %, of the proceeds from the real estate asset sales that would be paid under the heading of the tax on capital gains if the real estate assets were to be sold by the firm in a given year.
Volume of Real Estate	Numbers of square meters normalised the net value of the balance sheet.

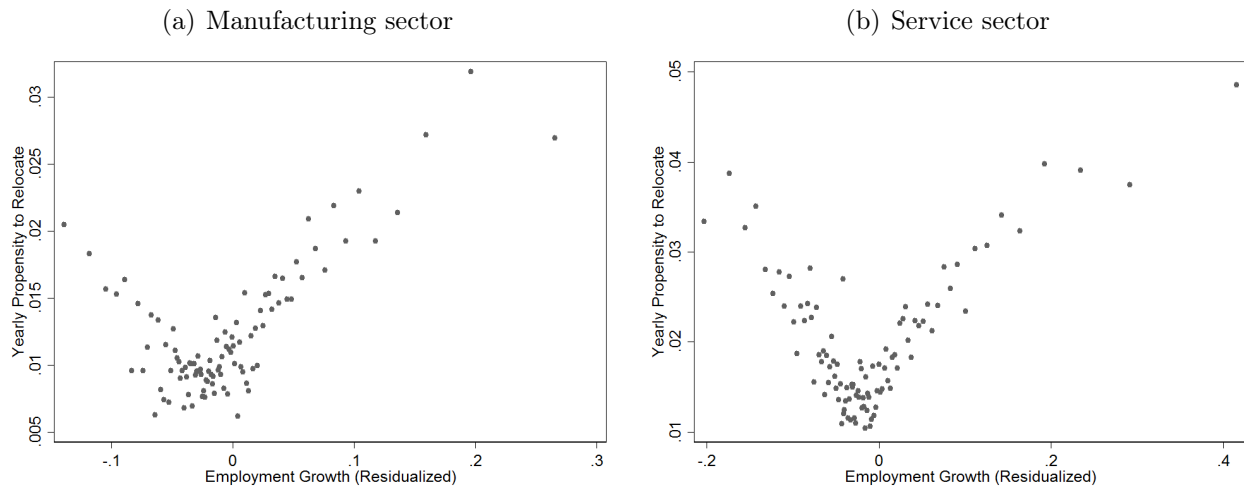
Notes: This table gives the definition of the variables used in the empirical analysis. For a detailed description of these variables construction, see appendix [C.1](#).

C.1.2.3 Variables description

Variable description and construction is summarized in [Table C.3](#).

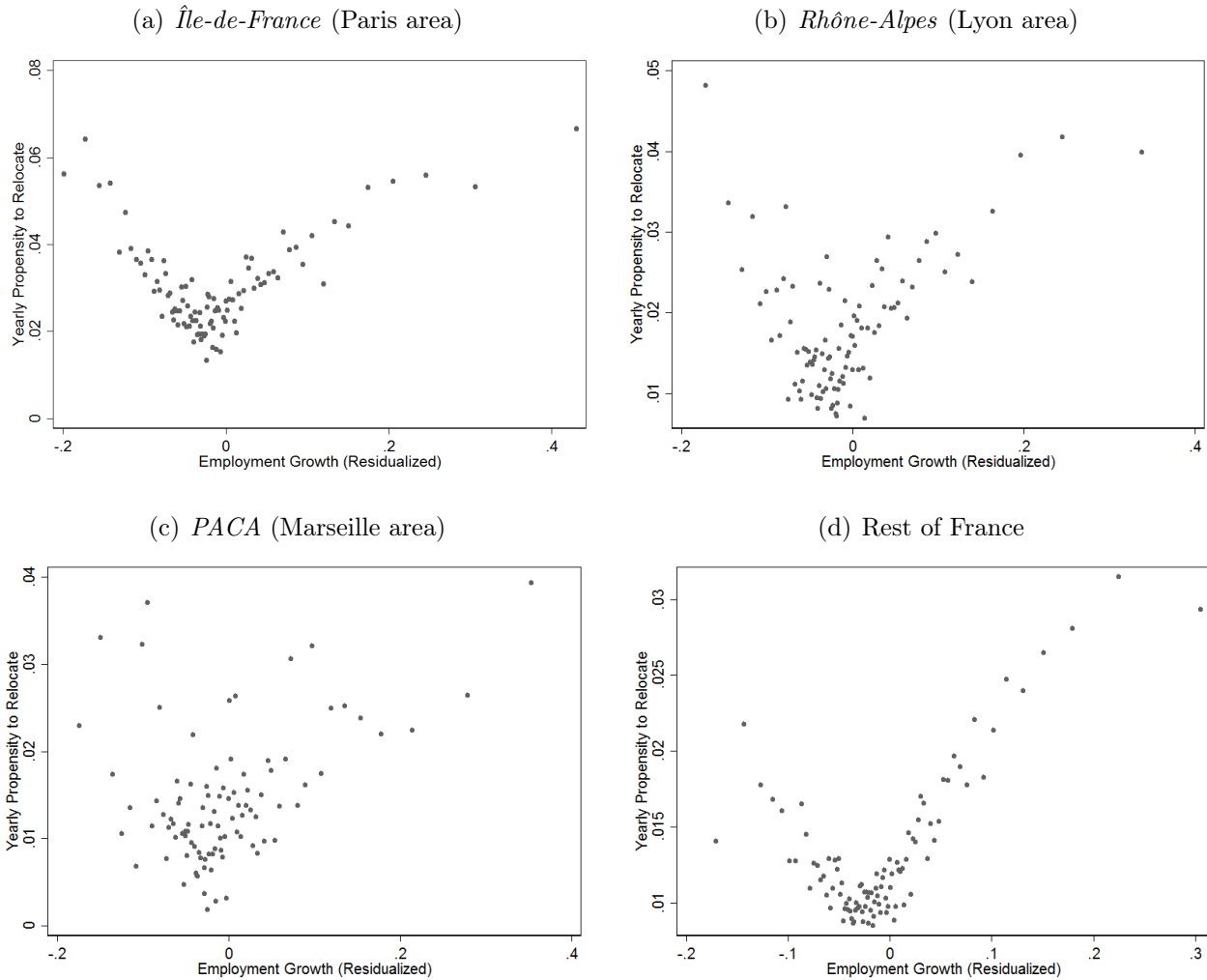
C.2 Additional figures

Fig. C.2: Propensity to relocate against employment growth - Manufacturing and Services



Notes: see Figure 4.1. Period of observation: 1994-2013. Left-hand side figure only includes observations from manufacturing industry while right-hand side figure only includes observations from the service industry. Source: FiBE_n.

Fig. C.3: Propensity to relocate against employment growth - Various regions



Notes: see Figure 4.1. Period of observation: 1994-2013. Lyon Area (Region *Rhone-Alpes*) includes d'epartements 01, 07, 26, 38, 42, 69, 73, 74). Paris Area (Region *Ile de France*) includes d'epartements 75, 77, 78, 91, 92 ,93 ,94 ,95). Marseille Area (Region *PACA: Provence-Alpes-Cote-d'Azur*) includes d'epartements 04, 05, 06, 13, 83, 84. Rest of France include all other d'epartements. Source: FiBEn.

C.3 Theory appendix

C.3.1 Model without friction

In a model without friction, each intermediate firm maximizes its revenue by choosing $r(i)$ and $l(i)$. First order conditions yields:

$$l(i) = \alpha \left[\frac{\Omega(i)(1-\varepsilon)}{w} \right]^{\frac{1}{\varepsilon}} \left(\frac{w}{u} \right)^{\frac{(1-\alpha)(1-\varepsilon)}{\varepsilon}} \quad (\text{C.1})$$

$$r(i) = (1-\alpha) \left[\frac{\Omega(i)(1-\varepsilon)}{u} \right]^{\frac{1}{\varepsilon}} \left(\frac{w}{u} \right)^{\frac{-\alpha(1-\varepsilon)}{\varepsilon}} \quad (\text{C.2})$$

which implies that firm i 's output price is a fixed markup over its marginal costs:

$$p(i) = \frac{1}{1-\varepsilon} \frac{w^\alpha u^{1-\alpha}}{\theta(i)} \quad (\text{C.3})$$

and hence:

$$P = \frac{1}{1-\varepsilon} (w^\alpha u^{1-\alpha}) \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}} \quad (\text{C.4})$$

We can then write:

$$y(i) = \theta(i) [\Omega(i)(1-\varepsilon)]^{\frac{1}{\varepsilon}} (w^\alpha u^{1-\alpha})^{\frac{-1}{\varepsilon}} = \theta(i)^{\frac{1}{\varepsilon}} (1-\varepsilon)^{\frac{1}{\varepsilon}} Y P^{\frac{1}{\varepsilon}} (w^\alpha u^{1-\alpha})^{\frac{-1}{\varepsilon}} \quad (\text{C.5})$$

using the value of P yields:

$$y(i) = \theta(i)^{\frac{1}{\varepsilon}} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{1}{\varepsilon-1}} Y \quad (\text{C.6})$$

from the FOCs, note that

$$wl(i) + ur(i) = \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} w^\alpha u^{1-\alpha} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{1}{\varepsilon-1}} Y \quad (\text{C.7})$$

on the other hand:

$$p(i)y(i) = \frac{w_t^\alpha u^{1-\alpha}}{1-\varepsilon} \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{1}{\varepsilon-1}} Y \quad (\text{C.8})$$

We then show that the profit is equal to the production up to a markup

$$\pi(i) = \frac{\varepsilon}{1-\varepsilon} (w^\alpha u^{1-\alpha}) \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{1}{\varepsilon-1}} Y \quad (\text{C.9})$$

and

$$\int_0^1 \pi(i) di = \frac{\varepsilon}{1-\varepsilon} (w^\alpha u^{1-\alpha}) \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{\varepsilon}{\varepsilon-1}} Y \quad (\text{C.10})$$

From market clearing condition

$$\begin{aligned} L_s &= \int_0^1 l(i) di \\ R_s &= \int_0^1 r(i) di \\ PY &= \int_0^1 p(i) y(i) di, \end{aligned} \quad (\text{C.11})$$

we can show that in equilibrium:⁹

$$Y = \left(\frac{L_s}{\alpha} \right)^\alpha \left(\frac{R_s}{1-\alpha} \right)^{1-\alpha} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\frac{\varepsilon}{1-\varepsilon}} \quad (\text{C.12})$$

plugging into $\Omega(i)$ yields:

$$(1-\varepsilon)\Omega(i) = \theta(i)^{1-\varepsilon} \left(\frac{L_s}{\alpha} \right)^{\varepsilon\alpha} \left(\frac{R_s}{1-\alpha} \right)^{\varepsilon(1-\alpha)} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{\varepsilon} (w^\alpha u^{1-\alpha}). \quad (\text{C.13})$$

we can rewrite:

$$l_t(i) = \theta_t(i)^{\frac{1-\varepsilon}{\varepsilon}} \left(\frac{L_s}{\alpha} \right)^\alpha \left(\frac{R_s}{1-\alpha} \right)^{(1-\alpha)} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di \right)^{-1} \left(\frac{u}{w} \right)^{1-\alpha} \quad (\text{C.14})$$

⁹This result comes from the fact that the market clearing condition implies: $YP = \int_0^1 p(i)y(i)di$ and that $\frac{L_s}{R_s} = \frac{l(i)}{r(i)}$.

We know that $\frac{r(i)}{l(i)} = \frac{R_s}{L_s} = \frac{(1-\alpha)w}{\alpha u}$, hence:

$$l(i) = \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} \left(\frac{L_s}{\alpha}\right)^\alpha \left(\frac{R_s}{1-\alpha}\right)^{(1-\alpha)} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di\right)^{-1} \left(\frac{L_s}{\alpha}\right)^{1-\alpha} \left(\frac{R_s}{1-\alpha}\right)^{\alpha-1} \quad (\text{C.15})$$

Finally:

$$l(i) = \frac{\theta(i)^{\frac{1-\varepsilon}{\varepsilon}}}{\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di} L_s \text{ and } r(i) = \frac{\theta(i)^{\frac{1-\varepsilon}{\varepsilon}}}{\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di} R_s \quad (\text{C.16})$$

Normalizing P to 1 ; we obtain:

$$u = (1 - \varepsilon) \frac{1 - \alpha}{R_s} Y \quad (\text{C.17})$$

and

$$w = (1 - \varepsilon) \frac{\alpha}{L_s} Y \quad (\text{C.18})$$

and

$$p(i) = \frac{1}{\theta(i)} \left(\int_0^1 \theta(i)^{\frac{1-\varepsilon}{\varepsilon}} di\right)^{\frac{\varepsilon}{1-\varepsilon}} \quad (\text{C.19})$$

C.3.2 Existence of an interval of inaction

The relocating condition $d = \pi^1 - \pi^0 > 0$ is a function of Δ_r and we have:

$$d(\Delta_r) = \frac{u}{(1-\alpha)(1-\varepsilon)} \left(\varepsilon(1 + \Delta_r) - (1 - \alpha(1 - \varepsilon)) (1 + \Delta_r)^{\frac{\varepsilon}{1-\alpha(1-\varepsilon)}} \right) + u - a. \quad (\text{C.20})$$

The function d is differentiable and continuous in Δ_r . It is straightforward to show that d is decreasing with Δ_r when $\Delta_r < 0$ and increasing with Δ_r when $\Delta_r > 0$. The function d takes the value $u - a$ when Δ_r equals -1 , $-a$ when Δ_r equals 0 and tends to the infinity when Δ_r tends to infinity. Hence, if $u > a$, there exist only two values of Δ_r , one being negative and the other positive, such that $d = 0$. We denote them Δ_r^- and Δ_r^+ , respectively. The function d is negative when Δ_r is between Δ_r^- and Δ_r^+ and positive otherwise. Then, Δ_r^- and Δ_r^+ are the bounds of the non-relocating interval. We can easily show that $|\Delta_r^-|$ and $|\Delta_r^+|$ are increasing in a .

We explore further the properties of the bounds of the non-relocating interval when Δ_r is close to 0 using a third-order local approximation of the function d around 0 .

$$d(\Delta_r) = 0 \Leftrightarrow \frac{2((1-\alpha)(1-\varepsilon)) + \varepsilon}{3(1-\alpha(1-\varepsilon))} \Delta_r^3 - \Delta_r^2 + \frac{2a(1-\alpha(1-\varepsilon))}{u\varepsilon} \approx 0 \quad (\text{C.21})$$

Let us denote P the above-derived polynomial of degree 3. We can easily show that P' is negative when Δ_r is between 0 and $\frac{2(1-\alpha(1-\varepsilon))}{2(1-\varepsilon)(1-\alpha)+\varepsilon}$ and positive otherwise. P goes to $-\infty$ in $-\infty$ and to $+\infty$ in $+\infty$. We can also show that $P(0) > 0$ and $P\left(\frac{2(1-\alpha(1-\varepsilon))}{2(1-\varepsilon)(1-\alpha)+\varepsilon}\right) < 0$ when $u \gg a$. Then, P has three real roots, λ_1 , λ_2 and λ_3 with $\lambda_1 < 0 < \lambda_2 < \lambda_3$. The two roots that are solutions to our problem $\pi^1 - \pi^0 = 0$ are λ_1 and λ_2 and λ_3 is only an artifact due to the third order approximation generating large error as Δ_r is far from 0 . We know from usual properties of polynomials on degree 3 that:

$$\begin{aligned} \lambda_1 + \lambda_2 + \lambda_3 &= \frac{3(1-\alpha(1-\varepsilon))}{2((1-\alpha)(1-\varepsilon))+\varepsilon} \\ \lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3 &= 0 \\ \lambda_1\lambda_2\lambda_3 &= \frac{-6a(1-\alpha(1-\varepsilon))^2}{u\varepsilon(2(1-\alpha)(1-\varepsilon)+\varepsilon)} \end{aligned} \quad (\text{C.22})$$

From which we obtain:

$$\lambda_1 + \lambda_2 = (\lambda_1 \lambda_2)^2 \frac{u\varepsilon(2(1-\alpha)(1-\varepsilon) + \varepsilon)}{6a(1-\alpha(1-\varepsilon))^2} > 0 \quad (\text{C.23})$$

which implies $|\Delta_r^+| > |\Delta_r^-|$.

We also have:

$$\sqrt{\lambda_1 + \lambda_2}^3 = \sqrt{\lambda_1 + \lambda_2} \frac{2((1-\alpha)(1-\varepsilon)) + \varepsilon}{3(1-\alpha(1-\varepsilon))} + \sqrt{\frac{6a(1-\alpha(1-\varepsilon))^2}{u\varepsilon(2(1-\alpha)(1-\varepsilon) + \varepsilon)}} \quad (\text{C.24})$$

From which we deduce that $\sqrt{\lambda_1 + \lambda_2}$ is increasing in a and decreasing in ε .

C.3.3 Results from simulation: the case of a positive aggregate productivity shock (+5%)

Fig. C.4: Employment growth as a function of productivity shocks for different values of a -5% shock

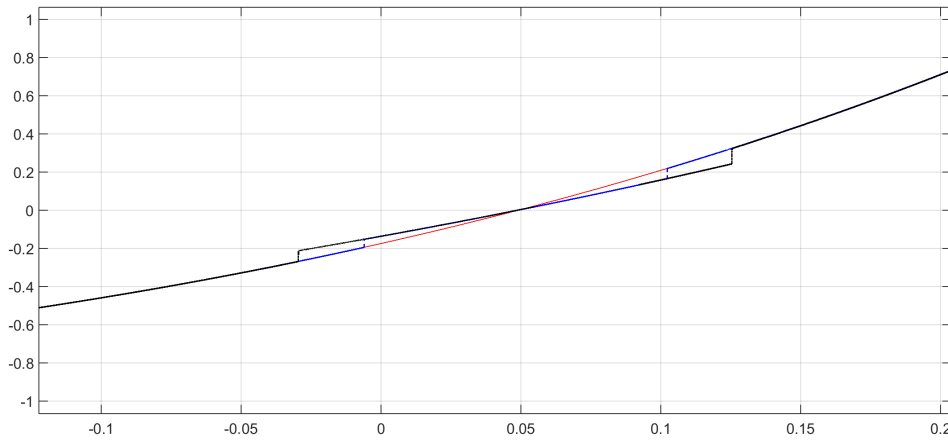
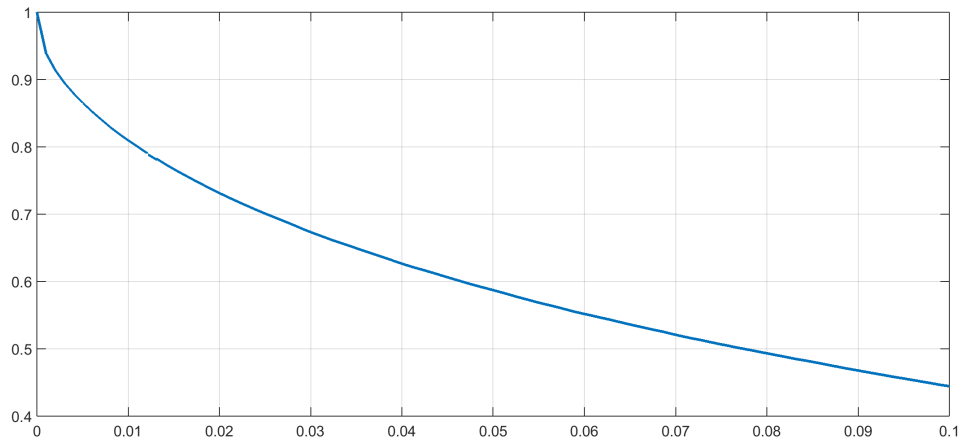
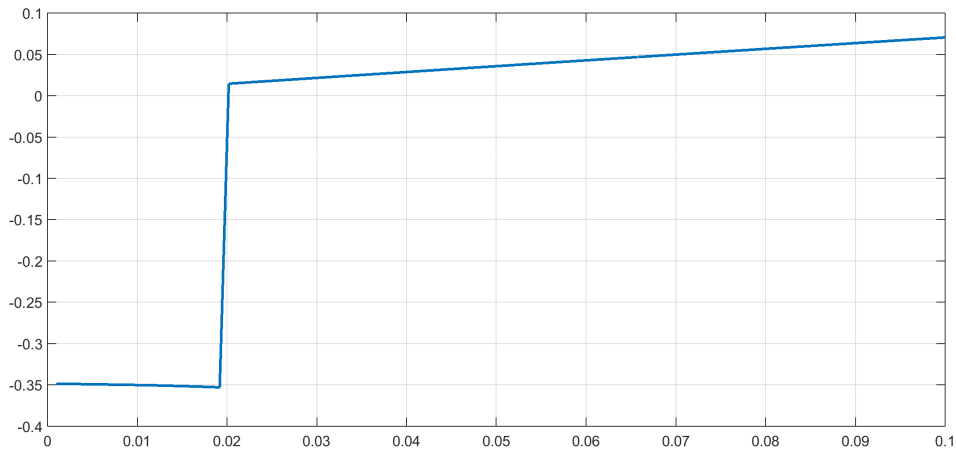


Fig. C.5: Share of relocating firms - 5% shock



Notes: This figure plots the share of firms that optimally choose to relocate for different values of a . Aggregate productivity shock: +5%.

Fig. C.6: Length of the non-relocating interval - 5% shock



Notes: This figure plots the difference between the smallest positive percentage change in real estate size that triggers relocation and the absolute value of the largest negative percentage change that triggers relocation for different values of a - aggregate productivity shock: +5%.

Fig. C.7: Mean employment growth as a function of a - 5% shock

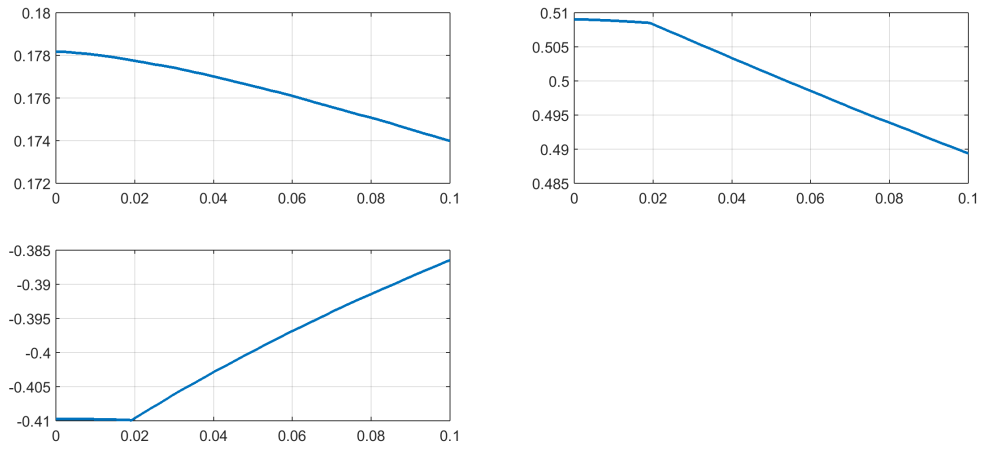
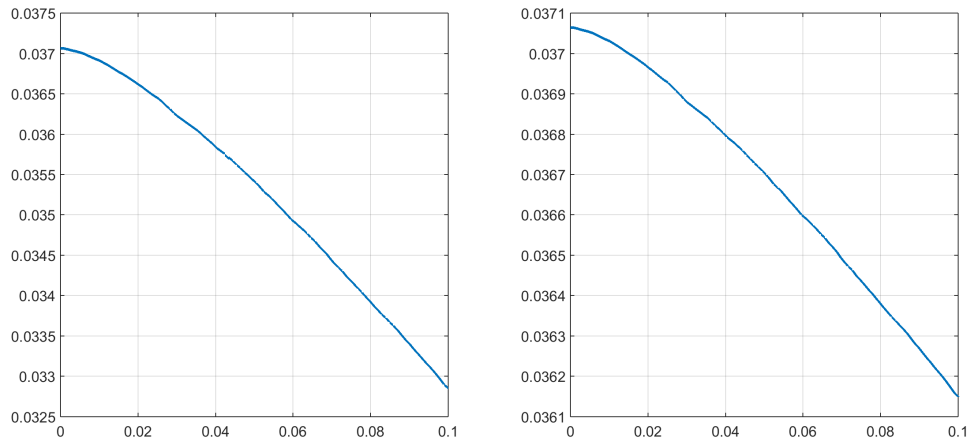
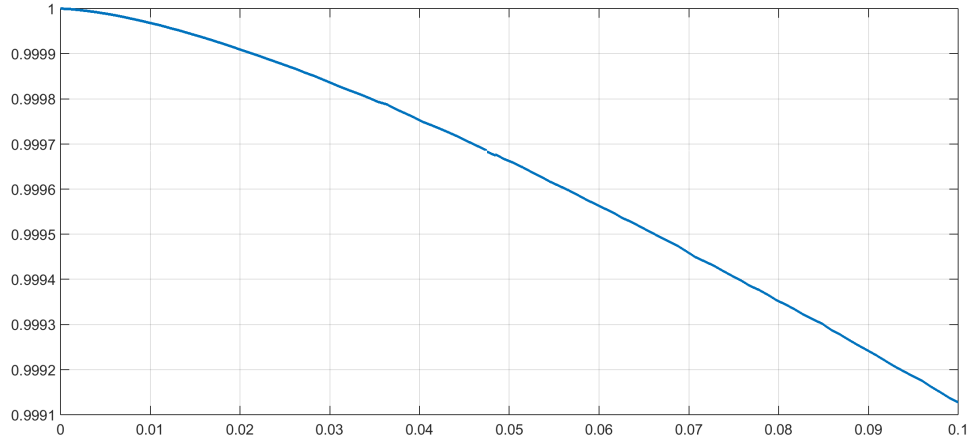


Fig. C.8: Covariance between real-estate volume and relocation cost - 5% shock



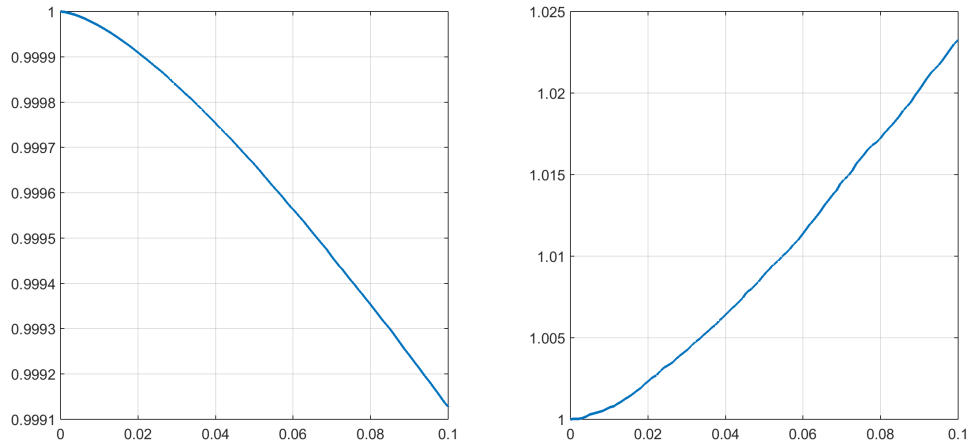
Notes: This figure plots the covariance between $r(i)$ and $\theta(i)$ as a function of a - aggregate productivity shock: +5%.

Fig. C.9: Aggregate output as a function of a



Notes: This figure plots the the value of Y as a function of a - aggregate productivity shock: +5%.. Standardized at 1 for $a = 0$.

Fig. C.10: Inputs' price as a function of a - 5% shock



Notes: This figure plots the equilibrium value of p as a function of a - aggregate productivity shock : +5%. Standardized at 1 for $a = 0$.

C.4 Additional empirical results

C.4.1 Robustness of results in section 4.4.1

Different definition of local relocations

In our baselines methods, we have defined a relocation to be “local” if the distance between the municipalities of departure and the municipalities of arrival is below 15km. As shown in Figure C.1, this corresponds to a large share of all the inter-municipalities relocations we see in the data. Table C.4 also shows that increasing this threshold only marginally change the frequency of relocations, both for real-estate owners and renters.

Table C.4: Frequency of relocations

	Share of relocating firms	
	Owners	Renters
Distance < 15km	10.8%	18.0%
Relocations from 15km to 25km	1.6%	2.4%
Relocations from 25km to 35km	0.7%	0.9%
Other relocations	2.8%	2.8%
Within Labor Market Area relocations	9.0%	13.1%

Notes: This table present the share of firms that have relocated at least once from 1994 to 2013. Relocations is split into four categories: local relocation (up to a distance of 15km), relocations at a distance ranging between 15 and 25km, relocations at a distance ranging between 25 and 35km, relocations at a distance above 35km and relocation within a Labor Market Area (*Zone d'Emploi*).

In Tables C.5, C.6 and C.7, we run OLS estimation of equation (4.14) respectively for all firms, growing firms and declining firms. In each of these three tables, column 1 uses our baseline threshold of 15km, column 2 and 3 use thresholds of 25km and 35km respectively and column 4 consider a relocation to be “local” if it is done within a *Zone d'Emploi* (Labor Market Area).

Table C.5: Relocation and employment dynamics - All firms - Different distance thresholds - Cross section OLS

Dependent variable: Yearly average employment growth (in %)				
Threshold	All firms			
	15km (1)	25km (2)	35km (3)	<i>Zone d'Emploi</i> (4)
Relocate	0.069*** (0.020)	0.072*** (0.019)	0.104*** (0.035)	0.110** (0.052)
Age	-0.081*** (0.004)	-0.081*** (0.004)	-0.080*** (0.004)	-0.081*** (0.004)
Size	-3.904* (2.178)	-3.902* (2.178)	-3.915* (2.183)	-3.875* (2.170)
R ²	0.057	0.058	0.058	0.058
Observations	118,980	118,980	118,980	118,980

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km in column 1, below 25km in column 2, below 35km in column 3 and within a Labor Market Area in column 4) in % from 1994 to 2013. Regressions include a *département* \times *sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département* \times *sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table C.6: Relocation and employment dynamics - Growing firms - Different distance thresholds - Cross section OLS

Dependent variable: Yearly average employment growth (in %)				
Threshold	Growing firms			
	15km (1)	25km (2)	35km (3)	<i>Zone d'Emploi</i> (4)
Relocate	0.157*** (0.037)	0.165*** (0.035)	0.230*** (0.070)	0.259** (0.104)
Age	-0.122*** (0.008)	-0.121*** (0.008)	-0.120*** (0.008)	-0.121*** (0.008)
Size	-8.121** (3.282)	-8.119** (3.281)	-8.092** (3.276)	-8.132** (3.277)
R ²	0.108	0.108	0.109	0.108
Observations	56,983	56,983	56,983	56,983

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. All columns restrict to firm with an overall positive employment growth in their observation period. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km in column 1, below 25km in column 2, below 35km in column 3 and within a Labor Market Area in column 4) in % from 1994 to 2013. Regressions include a *département*×*sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table C.7: Relocation and employment dynamics - Declining firms - Different distance thresholds - Cross section OLS

Dependent variable: Yearly average employment growth (in %)				
Threshold	Declining firms			
	15km (1)	25km (2)	35km (3)	<i>Zone d'Emploi</i> (4)
Relocate	-0.103*** (0.010)	-0.098*** (0.009)	-0.097*** (0.009)	-0.113*** (0.011)
Age	0.020*** (0.001)	0.020*** (0.001)	0.020*** (0.001)	0.021*** (0.001)
Size	4.485*** (1.725)	4.460*** (1.711)	4.481*** (1.722)	4.245*** (1.632)
R ²	0.156	0.156	0.156	0.155
Observations	46,605	46,605	46,605	46,605

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. All columns restrict to firm with an overall negative employment growth in their observation period. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km in column 1, below 25km in column 2, below 35km in column 3 and within a Labor Market Area in column 4) in % from 1994 to 2013. Regressions include a *département*×*sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Considering different time periods

In our baseline regression presented in Table 4.3, we take all the characteristics of the firms in the first year it appears in the data. However, this year can be different across firms, especially for those who enter the dataset between 1994 and 2013. In this section, we show that our results are only marginally affected if we (i) restrict to firms that enter the dataset in 1994 (that is we do not consider entry); (ii) restrict to the first five years following entry in the dataset when computing aggregate employment and the frequency of relocation. These results are respectively presented in Tables C.8 and C.9.

Table C.8: Relocation and employment dynamics - No entry - Cross section OLS

Dependent variable: Yearly average employment growth (in %)			
	All (1)	Growing (2)	Declining (3)
Relocate	0.092*** (0.022)	0.193*** (0.044)	-0.070*** (0.010)
Age	-0.053*** (0.004)	-0.069*** (0.008)	0.006*** (0.002)
Size	-19.408 (23.539)	-30.184 (32.259)	5.674 (9.926)
R ²	0.112	0.218	0.203
Observations	43,550	19,985	20,446

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. All columns exclude firms with a first year of observation that is higher than 1994. Column 1 uses all firms, column 2 (resp. 3) restricts to firms with positive (resp. negative) employment growth. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Regressions include a *département* \times *sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département* \times *sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Agglomeration effect

In Table C.10, we compare the characteristics of the municipalities of departure and destination for both growing and declining firms. We see that overall, firms relocate to smaller and less dense areas that where their sector is more concentrated and larger. However, we do not observe any significantly different behaviour across the two groups of firms except as far as density is concerned. The difference in density disappear when the Paris area is excluded from the sample.

Table C.9: Relocation and employment dynamics - First Five Years - Cross section OLS

Dependent variable: Yearly average employment growth (in %)			
	All (1)	Growing (2)	Declining (3)
Relocate	0.104*** (0.015)	0.210*** (0.027)	-0.078*** (0.006)
Age	-0.102*** (0.005)	-0.140*** (0.009)	0.022*** (0.001)
Size	-5.821** (2.788)	-11.646*** (4.164)	6.328** (2.620)
R ²	0.052	0.105	0.166
Observations	128,310	65,240	42,168

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the first five years of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. Column 1 uses all firms, column 2 (resp. 3) restricts to firms with positive (resp. negative) employment growth. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km) in % during the first five years of observation. Regressions include a *département*×*sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Place based program

The displacement effect of publicly funded place-based programs has been documented in recent contributions (Givord et al. (2013); Mayer et al. (2015) for the French *ZFU*s (*Zone Franche Urbaine*) and Overman and Einio (2012) for the Local Enterprise Growth Initiative in the UK which shares similarities with the French program). Those programs are often blamed for causing a shift of economic activity from areas that do not benefit from the program to areas that do. In turns, this mechanism could offer an alternative explanation to the linkages between workforce growth and local relocations; that is to say an explanation that do not rely on premises' size constraint. If firms relocate in order to benefit from a more generous tax system that enables them to increase their workforce, we would observe a positive correlation

Table C.10: Statistics on changes in local characteristics following a relocation - Growing firms and declining firms

	Mean		Difference
	Declining firms	Growing firms	
Population	-52.4	-41.9	-10.5 (8.15)
Density	-0.80	-0.67	-1.28** (0.65)
Herfindahl index	0.021	0.016	0.004 (0.005)
Local sectoral size	0.017	0.019	-0.002 (0.006)
Nb of obs.	7,634	11,215	-

Notes: This table shows the mean changes in some local characteristics following a relocation. We differentiate the firms for which we observed an overall increase in the headcount from firms for which we observe a overall decline in the headcount. The statistics reported correspond the difference between the value observed in the municipality of settlement in the year of the relocation and the value observed in the municipality of departure prior to the relocation. Population is in thousands inhabitants in 1990 at the municipality level. Density, at the municipality level, in thousands inhabitants per square kilometer. The Herfindahl index is computed at the 2-digit sector×municipality×year level. Finally, the local sectoral size is the sum of the sales at the 2-digit sector×municipality×year level. The Period of observation: 1994-2013. Source: INSEE and FiBE_n, see section C.1 for more detail about the data.

between the occurrence of a local relocation and an increase in the workforce. Note, however, that this mechanism would not be able to account for the left branch in the documented U-shaped relationship between employment growth and location relocation presented in Figure 4.1. We check that this alternative mechanism does not alter our main results by excluded from our database firms that are located less than 15km away from a *ZFU*.¹⁰ In doing so, we discard all the potential relocation that could conduct a firm to relocate to a *ZFU*s. In columns 1 to 3 of Table C.11 we estimate equation (4.14) with this restricted sample. We find no difference compared to our baseline results.

Table C.11: Relocation and employment dynamics - No entry - Cross section OLS

Dependent variable: Yearly average employment growth (in %)			
	All (1)	Growing (2)	Declining (3)
Relocate	0.126*** (0.018)	0.214*** (0.031)	-0.067*** (0.010)
Age	-0.063*** (0.004)	-0.103*** (0.010)	0.021*** (0.002)
Size	-34.011*** (10.651)	-117.888*** (32.818)	19.633*** (7.569)
R ²	0.082	0.145	0.206
Observations	66,858	32,028	25,881

Notes: The dependent variable, average employment growth, is measured as the mean of yearly employment growth over the period of observation and given in %. Variables definitions are given in Table C.3. Age and Size are taken in the first year the firm appears in the database. All columns exclude firms located less than 15km from a *ZFU*. Column 1 uses all firms, column 2 (resp. 3) restricts to firms with positive (resp. negative) employment growth. Relocate is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Regressions include a *département*×*sector* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

¹⁰An alternative would consist in focusing on big firms. There are indeed size restrictions to be eligible to the favorable tax scheme offered within the limits of a *ZFU*; in particular, firms with headcount higher than 50 are not eligible. There is also often a less stringent criterion related to total sales. Nevertheless, our study being conducted on single establishment firms, this would restrict our database to a small number of observations.

C.4.2 Additional results

Difference between owners and renters

Table C.12 shows the difference between real-estate owning firms and renters. We see that the latter are significantly smaller, younger and grow faster than the former. Real-estate renters also relocate more frequently which is consistent with the view that they face lower moving costs than real-estate owners.

Table C.12: Summary statistics - Owners and Renters

	Mean		Difference	
	Owners	Renters		
Employment	26.8	15.8	11.0***	(0.14)
Sales	3.88	2.49	1.39***	(0.043)
BS Size	2.75	1.76	0.99***	(0.14)
Age	18.6	10.6	8.1***	(0.079)
Employment growth	1.6%	3.7%	-2.1%***	(0.099)
Frequency of Relocation	1.2%	2.5%	-1.3%***	(0.034)
Nb of obs.	46,034	78,109	-	

Notes: This table shows the mean of different key variables, in initial year of observation, for firms that own their real-estate (Owners) and for firms that rent their real-estate (Renters). Employment is given in full-time equivalent (FTE) number of workers as reported by the firm; Employment growth in the mean yearly percentage change in FTE over the observation period; Sales are in millions of euros; BS size is the net value of the assets reported in the balance sheet and is given in millions of euros; Profits is the Earning Before Interest and Tax margin (i.e., EBIT to Sales ratio); Age is the number of year since company's incorporation; Frequency of Relocation is the number of local relocation divided by the number of years of observation for the firm. Source: FiBEn, see Appendix C.1 for more detail about the data. The latest column show the mean and standard deviation of the difference between the two coefficients and the Student t-stat on the nullity of this difference. ***, ** and * indicate that the null hypothesis of this test is rejected at the 1%, 5% and 10% level of significance.

Changes in the samples

In Table C.13, we remove from the sample all the firms that switch from renters to owners (and conversely) as they locally relocated. There are 0.58% of the firms that changed their tenure status from owner to renter and 1.44% that do the opposite. In any case, excluding these firms from the sample does not affect our results.

Table C.13: Relocation cost and relocation choice - Remove tenure status transition - Cross section OLS

	Dependent variable: Relocate					
	All		Owners			
	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Owner	-0.593*** (0.035)					
Tax		-1.960*** (0.465)	-2.101*** (0.472)	-2.549*** (0.544)	-2.752*** (0.562)	-2.059*** (0.565)
Age	-0.021*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.007*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Size	1.656 (1.728)	5.192* (3.062)	5.159* (3.065)	5.134* (3.058)	5.048* (2.933)	5.038* (2.938)
Volume Real Estate			-0.015*** (0.005)	-0.005 (0.004)	-0.003 (0.004)	-0.002 (0.004)
Age Real Estate				-0.023*** (0.004)	-0.021*** (0.005)	-0.019*** (0.005)
R ²	0.091	0.121	0.121	0.122	0.159	0.158
Observations	118,515	44,999	44,999	44,274	44,274	44,274

Notes: The dependent variable, Relocate, is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Variables definitions are given in Table C.3. All single-establishment firms that do not change their tenure status are considered. Column 1 uses all of these firms while columns 2 to 5 restrict to real estate owners. The dependent variable is a binary variable equal to 1 if the firm has locally relocated (with a distance below 15km) from 1994 to 2013. Other variables are taken in the first year of observation. Regressions include a *département*×*sector* fixed effect. Column 5 adds a *département*×*first year of observation* fixed effect. Column 6 uses an alternative proxy for the latent tax on capital gain built from national price level. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

In Table C.14, we remove from the sample all the firms that relocate to a city located farther than 15km away. Here again, results are only partially altered.

Table C.14: Relocation cost and relocation choice - Only local movers - Cross section OLS

	Dependent variable: Relocate					
	All		Owners			
	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Owner	-0.603*** (0.037)					
Tax		-2.227*** (0.484)	-2.379*** (0.491)	-2.592*** (0.548)	-2.770*** (0.571)	-2.004*** (0.596)
Age	-0.022*** (0.001)	-0.013*** (0.001)	-0.012*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Size	1.906 (1.849)	6.881*** (2.262)	6.842*** (2.268)	6.501*** (2.459)	6.414** (2.559)	6.409** (2.564)
Volume Real Estate			-0.016*** (0.005)	-0.005 (0.005)	-0.003 (0.005)	-0.002 (0.005)
Age Real Estate				-0.023*** (0.005)	-0.021*** (0.005)	-0.019*** (0.005)
R ²	0.095	0.128	0.128	0.128	0.166	0.166
Observations	112,853	43,103	43,103	42390	42,390	42,390

Notes: The dependent variable, Relocate, is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Variables definitions are given in Table C.3. All single-establishment firms that do not relocate to a distance over 15km are considered. Column 1 uses all of these firms while columns 2 to 5 restrict to real estate owners. The dependent variable is a binary variable equal to 1 if the firm has locally relocated (with a distance below 15km) from 1994 to 2013. Other variables are taken in the first year of observation. Regressions include a *département*×*sector* fixed effect. Column 5 adds a *département*×*first year of observation* fixed effect. Column 6 uses an alternative proxy for the latent tax on capital gain built from national price level. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table C.15: Relocation cost and relocation choice - National level tax - Cross section OLS

Dependent variable: Relocate				
Owners				
	(1)	(2)	(3)	(4)
Tax	-1.882*** (0.485)	-2.001*** (0.489)	-2.030*** (0.542)	-2.180*** (0.588)
Age	-0.014*** (0.001)	-0.013*** (0.001)	-0.008*** (0.001)	-0.007*** (0.001)
Size	5.316* (2.901)	5.279* (2.904)	5.019* (2.989)	5.029* (2.863)
Volume Real Estate		-0.016*** (0.005)	-0.005 (0.005)	-0.003 (0.005)
Age Real Estate			-0.023*** (0.004)	-0.021*** (0.005)
R ²	0.121	0.121	0.121	0.160
Observations	45,181	45,181	44,412	44,412

Notes: The dependent variable, Relocate, is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Variables definitions are given in Table C.3. All columns restrict to real estate owners. The dependent variable is a binary variable equal to 1 if the firm has locally relocated (with a distance below 15km) from 1994 to 2013. Other variables are taken in the first year of observation. Regressions include a *département*×*sector* fixed effect. Column 5 add a *département*×*first year of observation* fixed effect. Cross section OLS regression with robust standard errors clustered at the *département*×*sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table C.16: Relocation cost and relocation choice - Cross section OLS - Within Labor Market Area relocations.

	Dependent variable: Relocate					
	All	Owners				
	(1)	(2)	(3)	(4)	(5)	(6)
Real Estate Owner	-0.463*** (0.034)					
Tax		-2.079*** (0.457)	-2.263*** (0.464)	-2.871*** (0.527)	-2.717*** (0.540)	-2.039*** (0.520)
Age	-0.019*** (0.001)	-0.012*** (0.001)	-0.011*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Size	-0.242 (0.568)	0.626 (1.062)	0.584 (1.058)	0.510 (1.051)	0.278 (0.975)	0.267 (0.978)
Volume Real Estate			-0.019*** (0.005)	-0.007* (0.004)	-0.006 (0.005)	-0.005 (0.005)
Age Real Estate				-0.027*** (0.005)	-0.023*** (0.005)	-0.021*** (0.005)
R ²	0.065	0.108	0.109	0.112	0.154	0.154
Observations	118,980	45,181	45,181	44,412	44,412	44,412

Notes: The dependent variable, Relocate, is equal to the yearly frequency of local relocation (with a distance below 15km) in % from 1994 to 2013. Variables definitions are given in Table C.3. Column 1 uses all firms while columns 2 to 5 restrict to real estate owners. The dependent variable is a binary variable equal to the yearly frequency of relocation within the same *Zone d'Emploi* (Labor Market Area) in % from 1994 to 2013. Other variables are taken in the first year of observation. Regressions include a *département* \times *sector* fixed effect. Column 5 adds a *département* \times *first year of observation* fixed effect. Column 6 uses an alternative proxy for the latent tax on capital gain built from national price level. Cross section OLS regression with robust standard errors clustered at the *département* \times *sector* level reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

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