

Technological Change and Domestic Outsourcing*

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Abstract

Domestic outsourcing has grown substantially in developed countries over the past two decades. While some studies document its implications for earnings inequality, very little is known regarding the drivers of this phenomenon. This paper addresses this question by studying the impact of the staggered diffusion of broadband internet on job outsourcing by French firms. We adopt an event study design and rely on employer-employee data. Our results confirm that broadband technology is skill-biased, since it increases firm productivity and the relative demand for high-skill workers. Further, we show that broadband internet led firms to outsource some non-core occupations to service contractors, both in the low and high skill segment. In both cases, we find that employment related to these occupations became increasingly concentrated in firms specializing in these activities, and less likely to be performed in-house within firms specialized in other activities. Moreover, establishments become increasingly homogeneous in their occupational composition after the arrival of broadband internet, signaling that this technology fostered skill segregation. Finally, we provide suggestive evidence that high-skill workers experience salary gains from being outsourced, while low-skill workers lose.

JEL classification: L22, L23, O33

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1 Introduction

The implications of international outsourcing (or offshoring), i.e. the process of using a third-party firm based abroad to perform services that would otherwise be performed in-house by local employees, have been at the center of recurrent public debates and the focus of a large body of the economic research and policy analysis.¹ More recently, empirical work has highlighted the pervasiveness of *domestic* outsourcing among developed economies (Dube and Kaplan, 2010; Goldschmidt and Schmieder, 2017) and has started to document its implications for the distribution of earnings. However, this nascent literature is silent on the factors underlying these trends and in particular on whether this phenomenon is driven by institutional or technological changes.

In this paper, we look at the role played by innovation in information and communication technology (ICT) in fostering the rise of domestic outsourcing. To do so, we estimate the impact associated with the diffusion of a new general purpose technology—Broadband Internet—on employment outsourcing by French firms. To the extent that Broadband internet (BI hereafter) has reduced communication costs and information frictions, the diffusion of this technology is likely to have modified the optimal boundaries of firms, and affected the terms of the make or buy decisions that firms face (see e.g. Lewis and Sappington, 1991; Garicano and Rossi-Hansberg, 2006; Bloom et al., 2014; Aghion et al., 2019b). It is therefore natural to assess the impact it has had on the allocation of workers to firms, in particular through the rise of domestic outsourcing. BI is likely to directly improve the productivity of impacted firms through various channels, in a way that is biased toward workers with more formal education (Akerman et al., 2015) and those employed in more complementary occupations (Aghion et al., 2019a).

To better understand the impact of BI on the labor market, we use administrative data at the individual level on the universe of French workers from 1994 to 2010. This time interval covers the full roll-out of broadband connection across the French territory which essentially took place between 2000 and 2007. We first confirm the skill-bias impact of BI. As cities become progressively connected, we see that the share of high-skill (resp. low-skill) workers increase (resp. decrease) even after controlling for local observed and unobserved heterogeneity. We also show that workers in high-skill

¹See Hummels et al. (2018) for a review of recent empirical works and Biscourp and Kramarz (2007) for a seminal work on French administrative data.

occupations experience greater increase in their hourly wage than workers in low-skilled occupations following broadband deployment in the city where they work. These results are in line with [Akerman et al. \(2015\)](#) who study the effect of broadband expansion in Norway.

This evidence of skill-bias technological change is the result of important changes in employment across firms. We show further that BI led firms to outsource some non-core occupations to service contractors. Interestingly, outsourcing does not only affect low skilled occupations such as cleaners or drivers, but also some high skilled occupations. As an example, we show that following BI expansion both IT specialists and cleaners are increasingly concentrated in establishments specializing in these activities, and thus less likely to be performed in-house in establishments of different sectors.² Consistent with this evidence, we find that occupational segregation at the establishment level, as captured by an Herfindahl-Hirschman Index of concentration (HHI), is positively impacted by broadband expansion. This suggests that the pattern of reorganization of occupations across firms is broader than the process we directly and most precisely document in the case of cleaning and IT occupations. This evidence also consistent with [Godechot et al. \(2020\)](#) who, based on administrative data in several high-income countries, document a steep increase in both earnings and occupational segregation at work which, regarding occupation, is particularly pronounced in France.³

Previous works investigating the impact of outsourcing on earnings have mostly focused on low-wage occupations ([Goldschmidt and Schmieder, 2017](#)). However, understanding the implications of outsourcing for earnings inequality also requires to study its impact on the higher end of the income distribution. We implement an event-study design at the establishment and individual-level around outsourcing events— independently of whether they are induced by broadband or not—, in order to estimate the effect of outsourcing on earnings of workers employed in both high- and low-skill outsourceable occupations. Our results suggest that the impact of domestic outsourcing is heterogeneous across skills: high-skill workers experience wage increase after being outsourced while low-skill workers see their wage decrease, implying that outsourcing tend to widen pre-existing disparities in earnings. This pattern of wages changes in the aftermath of outsourcing transition is consistent with these

²The choice of these two occupations was driven by the fact that these two categories are relatively large in size (and thus present in many municipalities), and are easy to isolate in the occupation and sector classification.

³See their Figure S8.

transitions corresponding to voluntary moves for high-skill workers and involuntary ones with low-skill workers.

The analysis in this paper contributes to several strands of literature. First we relate to a small empirical literature exploiting BI expansion as a plausibly exogenous technological and informational shock. In France, [Malgouyres et al. \(2019\)](#) show that the BI expansion was associated with an increase in imports by treated firms. Consistently, [Akerman et al. \(2018\)](#) show that BI narrows the role of distance in explaining bilateral trade in Norway. In the UK, [DeStefano et al. \(2018\)](#) find that a similar shock did not affect firms' productivity but only their size, which suggests that local institutions matter in explaining the effect of broadband expansion. More closely related to our study, [Akerman et al. \(2015\)](#) evaluate the skill-bias of BI in Norway. They find that broadband availability increases both firm productivity and the skill wage premium. We contribute to this literature by documenting the mechanism behind the the skill-bias of broadband internet. In particular, we show it operates through the reallocation of high and low-skill workers across firms and not only through a shift in the firm production function. These reorganizations affect heterogeneous workers in a way that amplifies preexisting wage inequalities.

Second, our paper is linked to the literature on domestic outsourcing. [Weil \(2014\)](#) describes how the nature of work has changed in the 21st century as a result of large companies switching to a "fissured workplace" business model. [Goldschmidt and Schmieder \(2017\)](#) show how Germany experienced an explosion of domestic outsourcing of low-skill non-core activities since the early 1990s.⁴ In their paper, outsourcing results in wage reduction for outsourced jobs, mainly driven by the loss of firm-specific rents. [Drenik et al. \(2020\)](#) have quantified this loss and show that the share of the firm-specific wage premium that outsourced worker earn is about half of the premium that insider earns. As a consequence, [Song et al. \(2019\)](#) underline how the increase in sorting and the segregation of low-skill workers contributed to the surge in income inequality. Technologies has also been related to outsourcing: using data on US firms, [Fort \(2017\)](#) shows that technology lowers the cost of coordination within a firm and leads to an increase in the fragmentation of production. [Aghion et al. \(2019a\)](#) characterise so-called "good jobs" that are protected from outsourcing as technology advances, even across low educated workers. We contribute to this literature in two main ways. First, we look explicitly at the effect of a specific tech-

⁴They focus on four emblematic activities: cleaning, logistics, security and food services and introduce an innovative measure to capture outsourcing of such tasks.

nology and by extend the spectrum of affected workers to high skilled occupations.⁵ Our estimate represents intent-to-treat as we do not track firm-level measure of actual ICT adoption. As such, our results complement the survey evidence (Abramovsky and Griffith, 2006) which points to a positive association between direct measures of firm-level ICT-intensity and the propensity to outsource and purchase services on the market. Second, we capture margin of adjustment largely ignored by the existing literature. While most works focus on either individual transitions from in-house to outsourced activities (Dube and Kaplan, 2010) or on plant-level outsourcing event (Goldschmidt and Schmieder, 2017), the rising prevalence of domestic outsourcing is likely to grow through the allocation of new entrants in the labor market to firms operating in the business services sector and the entry of new firms in such sectors. Our city-level approach analyzing the local evolution of the allocation of workers and occupations across firms in reaction to a change in the set of available technologies allows us to capture such margins.

Our paper is also more generally connected to the literature on technology and firm organization of labor. In France, Caliendo et al. (2015) analyze how the hierarchical structure changes as a firm grows, underlining the importance of considering layers when studying the dynamics of employment and wage. While they do not formally consider the role of technology, the role of new technologies on skill-biased organizational change has been documented in previous papers (see e.g. Autor et al., 2003; Michaels et al., 2014) and has been found to be associated with a reduction in the number of layers by increasing the “flatness” of the firm (Caroli and Van Reenen, 2001; Aghion et al., 2019a). The literature on the effects of ICT usually considers separately the effect of a reduction in the cost of communication and of the cost of information on the organizational structure of the firm (see e.g. Bloom et al., 2014). For instance, Garicano and Rossi-Hansberg (2006) makes a clear distinction between the cost of communication and the cost of acquiring knowledge. In their model, a reduction in communication cost fosters firm reorganization, where more problems are solved at the top of the hierarchy (typically by managers) and the knowledge content of production work shrink. Garicano (2000) and Borghans and Ter Weel (2006) describe how improved communication increases specialization of workers within the firm. In our paper we consider the effect of the reduction in both communication and

⁵Abramovsky et al. (2017) discuss the evolution of high skill occupations’ *offshoring*. The literature has also identified occupations that are more likely to be domestically outsourced to the growing business service sector, which can include some high-skill occupations such as advertisers, accountants, IT specialists and legal professionals (Ono, 2003; Berlingieri, 2014; Goldschmidt and Schmieder, 2017).

information costs brought about by BI on reorganization beyond the boundaries of the firm, through the sub-contracting of non-core activities to high and low-skill service providers.

Finally, our paper speaks to the literature on the mobility of workers and on the spatial sorting of skills induced by technological change. [Duranton and Puga \(2005\)](#) show that there is an increasing trend in the separation of management and production activities which leads to a specialization of occupations across firms and regions. This mechanism is part of a more global picture that led to the “Great Divergence of cities” ([Moretti, 2012](#)), whereby some cities became increasingly skill intensive and specialized while other remained essentially low-skilled. [Davis et al. \(2020\)](#) study this phenomenon in France, and link the great spatial divergence with technology-induced job polarization. They show that middle-pay jobs are replaced by low-pay jobs in small and medium cities, while high-pay jobs concentrate in the largest cities.⁶ The geographical specialization also occurs within sectors, where the increase in concentration at the national level is accompanied by the opposite trend at the local level, as shown by [Rossi-Hansberg et al. \(2018, 2019\)](#) for the US. In our paper, BI expansion induces geographical mobility within and between firms, which leads to a much greater spatial and sectoral specialization. Our results therefore echo recent findings in the literature which stress geographical heterogeneity in explaining recent trends in labor demand ([Eeckhout et al., 2019](#); [Autor, 2019](#); [Eckert et al., 2019](#)).

The rest of the paper is organized as follows. Section 2 present the data and our empirical methodology. Section 3 presents results regarding the effect of BI on shifts in skill demand. We then show in Section 4 that the skill-biased technical change effect is accompanied by the reorganization of firms that outsource some occupations. Finally, Section 5 looks more closely at the consequence of outsourcing on workers’ wage trajectory. Section 6 concludes.

2 Data and Institutional Context

2.1 Data

Administrative data on labor market outcomes. Our data come primarily from the French matched employer-employee dataset covering all workers based in France

⁶See also [Bonnet and Sotura \(2020\)](#) for an in-depth analysis of the long-run spatial disparities in France.

since 1994 (“*Déclaration Annuelle des Données Sociales*” or DADS). This dataset constitutes the primary source used to compute payroll tax data, and gives detailed individual information including salary, hours worked, occupation, age, gender, and the identifier of the employing firm and establishment. It is not possible to follow workers over time, except for a random sample of 1 over 24 workers which we refer to as the DADS panel. We clean these data and restrict our sample to the French private sector. Appendix B provides details about how we depart from the raw dataset.

One information that is usually missing from such administrative data is the individual level of education. Hence, we cannot control for skill level or ability based on this information. We therefore rely on occupation codes and classify workers into three categories as follows:

Definition 1.

- *Low-skilled workers.* Blue collar manual jobs in both industry or services sectors as well as administrative and sales clerks.
- *High-skilled workers.* White collar jobs including executives, managers and engineers.
- *Others.* Technicians and intermediate professions.⁷

Finally, to test the impact of broadband internet on firm productivity, we merge to the main data information relative to each business’ value added. The latter is taken from the administrative financial records made available by the French Ministry of Finance (“*Fichier Complet Unifié de Suse*” or FICUS), which report performance indicators for each private sector firm and it is available over the same period of time.⁸

Data on broadband expansion. Our main source of variation in technology availability derives from the expansion of broadband internet in France. The underlying data, described in details in [Malgouyres et al. \(2019\)](#), document the date of upgrading for each local exchange unit in mainland France.⁹ We additionally obtained data

⁷The formal definition of these groups is given in Appendix B and follows closely the classification adopted in [Caliendo et al. \(2015\)](#).

⁸This data cover the entire French private sector except from businesses operating in finance and insurance activities. It is reported at the level of the firm and it does not allow to disentangle between the performance of different establishments.

⁹Throughout the paper, broadband or ADSL refers to first generation ADSL that is associated with speed of 512 kbit/s. The historical operator was compelled by law to make this data available to other

from the regulatory agency (ARCEP) regarding the geographical coverage of each local exchange unit. Each city in France is partitioned into census-blocks, and the data documents the area of each census block (IRIS) that is covered by a given local exchange unit. Combining both datasets, we construct a continuous measure of broadband access of city i at year t . This measure, which we denote \tilde{Z}_{it} , is a time-weighted percentage of area covered in city i . It is formally defined as:

$$\tilde{Z}_{it} = \sum_{b \in i} D_{b,t} \frac{\mathcal{A}_{b,t}}{\sum_{b' \in i} \mathcal{A}_{b',t}}, \quad (1)$$

where $b \in i$ denotes the census tracks included in city i , $D_{b,t}$ share of the days of year t with access in b since January 1st of year t normalized by the number of days in year t . Finally, $\mathcal{A}_{b,t}$ denotes the area covered by census track b .

The variable \tilde{Z}_{it} is continuous with support between 0 and 1, reflecting both the area and time dimensions of local broadband availability.¹⁰ We refer to \tilde{Z}_{it} as the *degree of connection* of a city.

In our study of the dynamics of labor market following BI expansion, it will sometimes be useful to consider a discrete analog of \tilde{Z} . We follow [Malgouyres et al. \(2019\)](#) and define the year of treatment as $t_{i0} = \operatorname{argmax}_t \Delta \tilde{Z}_{it}$ and discretized treatment status as $Z_{it} = \mathbb{1}\{t \geq t_{i0}\}$. We denote $C_{i,t}$ the corresponding discrete (binary) variable. The discretization results in little loss of information, given the underlying distribution of the continuous variable, and allows us to implement transparent before/after comparison through the estimation of event-studies. We refer to the year corresponding to the largest change in the share of the municipality that is connected to the ADSL as the “year of connection”.¹¹ The latter ranges from 1999 for a handful of experimental cities to 2007 for the most remote areas.

operators as well as websites allowing consumers to gauge the quality of their line. The data was collected through one such website by [Malgouyres et al. \(2019\)](#) and validated manually.

¹⁰ \tilde{Z}_{it} will be equal to one if all of its areas have had access for the entire year. It will be equal to 1/2 if the entire city has had access to broadband over half the year t . In practice however, it is very strongly concentrated on 0 and 1, with very few intermediate observations, see Figure A1 in Appendix A.

¹¹Even if it does not mean that no one had access to the ADSL before this year in the municipality. Mainland France has up to 36,000 municipalities but most of them are very small and rural (the median population in 2010 is 427). Municipalities are grouped into counties (“*département*”), there are on average 381 municipalities per county.

2.2 The diffusion of Broadband Internet in France

As evidenced by [Malgouyres et al. \(2019\)](#), the deployment of the Broadband Internet technology beyond France’s largest cities was very slow at the beginning of the 2000’s and continued up to 2007. This was mostly due to legal, political and administrative reasons (see Appendix C for more details). Table C1 in Appendix shows percentage of cities and workers who were connected each year. In 2000, only 2% of cities were connected in 2000, although this corresponds to a much larger share of workers and establishments (respectively 25 and 22%). By 2003, 80% of workers are connected and 76% of establishments. At the end of 2005, 96% of French workers and 80% of cities are covered.

Explaining broadband expansion . Our identification strategy relies on the assumption that the coverage of cities was mostly determined by city population density—which is almost fixed over time and can be controlled for—and did not take into account underlying local trends in productivity or propensity to outsource activities. As a result, conditional on city and year fixed-effects, we consider the variation in broadband access to be as good as random. In order to assess the plausibility of this assumption, we explore the extent to which broadband coverage over time can be explained by different types of lagged city-level covariates. We group those covariates into two main groups:

1. **Density**: population in 1999 per square km (log), interacted with a full set of year dummy variables.
2. **Industry dynamics**: shares of employment in 10 economic sectors at $t - 1$ as well as changes in shares between $t - 1$ and $t - 2$.

We then estimate the following specification:

$$\tilde{Z}_{it} = \mathbf{dens}'_{it}\boldsymbol{\rho}_1 + \mathbf{indyn}'_{it}\boldsymbol{\rho}_2 + \text{FE}_i + \text{FE}_{r(i),t} + \varepsilon_{it}, \quad (2)$$

where \tilde{Z}_{it} is the time-weighted share of city i that is covered by broadband internet as described in Equation (1). As we are mostly interested in the explanatory power of these different groups of observable variables, we only report the R-square of each regression in Table 1.¹²

¹²Individual coefficients can be found in the Appendix Table C2.

Table 1: Explaining city broadband coverage: panel analysis

	(1)	(2)	(3)	(4)	(5)
	Covariates	Twoway FE	(2)+density	(2)+indus.	(2)+ all cov.
R^2	0.555	0.786	0.812	0.787	0.812
Industry: F-stat	50.73			2.57	2.18
Density: F-stat	21583.14		221.55		223.93

Notes : This table presents the R-square of panel regressions following equation (2). Twoway FE (Column 2) refers to a twoway fixed-effect model with city fixed effect and département \times year FEs. Density (Column 3) includes 1999 population density at the city level defined as total population divided by city area interacted with year indicators. Industrial structure controls (Column 4) include the lagged share and their changes of sectoral shares (nine sectors). Column (1) includes all of the controls without fixed effects.

Our results are summarized in Table 1. We start by regressing broadband internet coverage on all three sets of observable covariates without including any time or city fixed-effect. As indicated in Column (1) of Table 1, we obtain a R-square of 56% indicating that these variables capture a substantial share of the variation in treatment status. Column (2) presents the R-square of a two-way fixed-effect model including city and département \times year fixed effects. This model absorbs 78.6% of the variance in treatment intensity. Column (3) presents the same model to which we add the 1999 measure of density interacted with year dummies. The fit of the model increase by 2.6 pp. Interestingly, the set of industry dynamics variables barely increases the fit of the model (columns 4), indicating that, conditional on city and province-year fixed effect, they are roughly unrelated to the timing of internet coverage. Column (5) show that the F statistics associated with the null hypothesis that all of the industries variables are null is small (2.18) and two orders of magnitudes smaller than that associated with population density (223). We consider the low predictive power of observable variables as supporting our identification strategy, since a large share of the variation in timing of the broadband expansion seems to be idiosyncratic in nature.

3 BI Expansion and Skill-Biased Technological Change

In this section, we confirm and extend the results of [Akerman et al. \(2015\)](#) showing that broadband internet constitutes a skill-biased technology. In particular, we show that when a city becomes connected to BI (i) the labor productivity of establishments located in the city increases; (ii) the demand for high skill workers increases and (iii) the hourly wage and salary of high-skill workers increase.

3.1 At the city level

Technological change embedded in the gradual diffusion of broadband internet across municipalities is expected to be skill-biased, and in particular to increase firms' labor productivity and firms' demand for high-skill workers relative to the rest of the labor force. To identify a causal channel, we exploit the fact that the dissemination of the ADSL across municipalities was staggered over a period of nearly 10 years, from 1999 to 2007. We use the panel of cities c observed each year t from 1996 to 2007 to run the following econometric model:

$$Y_{c,t} = \sum_{\tau=-k}^{k'} \alpha_{\tau} \mathbb{1}\{t = t_c + \tau\} + \gamma_t \mathbf{X}_{c,t} + \nu_c + \varepsilon_{c,t}, \quad (3)$$

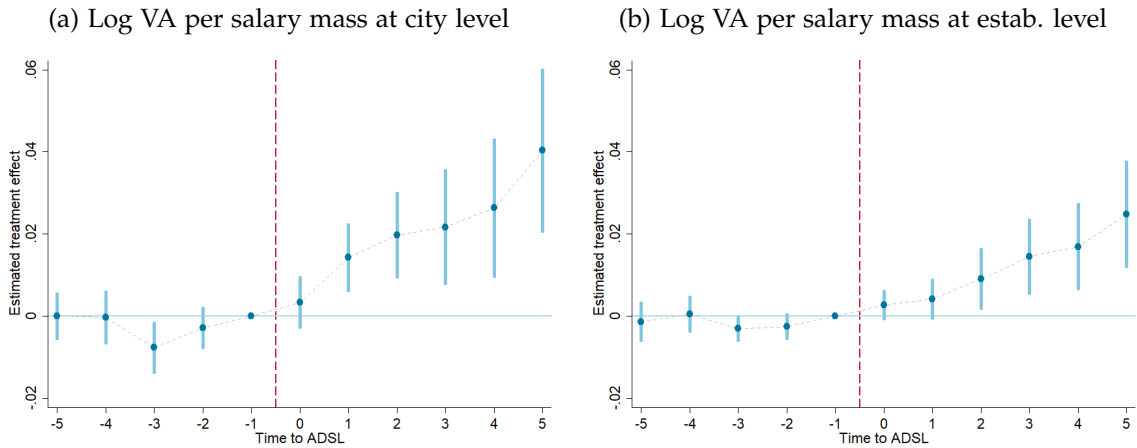
where Y is the variable of interest, t_c is the year of ADSL arrival of a city c and X is a vector of control variables. X contains a time unvarying measure of the density of the city in 1999 interacted with year dummies, the time-varying share of manufacturing employment and a set of department-year intercepts. Finally, we add city-level fixed effects such that the coefficients α_{τ} can be interpreted as changes within a given city resulting from the arrival of the ADSL, as compared to cities within the same department and with similar densities that have yet to be connected to BI. Standard errors are clustered at the department level. We exclude two dummies from the regression, respectively for $\tau = -1$ and $\tau = -6$ as suggested in [Borusyak and Jaravel \(2017\)](#) in this type of event study setting with year and individual fixed effects. The regression is run over the sample of cities that have more than 500 inhabitants at the beginning of the period, to avoid capturing an effect driven by small villages, and over the years 1997-2007, which include the full period of ADSL expansion.

Firm productivity We start by evaluating the impact that BI and the underlying ADSL technology had on firm productivity. Given that the financial data is only available at the company level, we restrict this analysis to single-establishment firms, for which it is possible to assign financial performance to a single location.¹³ We measure labor productivity as the log of value added divided by the total wage bill. At the city level, we consider the average productivity taken over the single-establishments

¹³An alternative would be to allocate the same labor productivity to each establishment within the same firm. If we do so, the effects remain qualitatively the same compared to our current methodology, but the coefficients become about 40% smaller and are significant at the 5% level instead of 1% level. Results are available upon request.

located in the municipality weighted by their size.¹⁴ Results obtained from both city and firm-level regressions are reported in Figure 1 and the corresponding coefficients are given in Table A4 in Appendix A. These findings confirm what was expected: BI increases the productivity of firms when the city in which they are located becomes connected. The average labor productivity of firms located in the city increases by about 2.5% over the first 5 years, and more than half of this effect (1.4%) takes place in firms already present in the area before the shock (see Table A4)¹⁵

Figure 1: Firm productivity and broadband access



Notes: This Figure shows regression coefficients and 95% confidence intervals from a dynamic event study where the dependent variable is the log of value added per salary mass within a city or establishment at t and the regressors are dummies for the number of years before/after broadband access. The outcome at the city level captures the weighted average of establishments in the city. Only mono-establishment firms are kept in the sample since value added data is only available at the aggregated firm level. Panel (a) follow the specification reported in equation 3, while panel (b) replaces city fixed effects by establishment fixed effects.

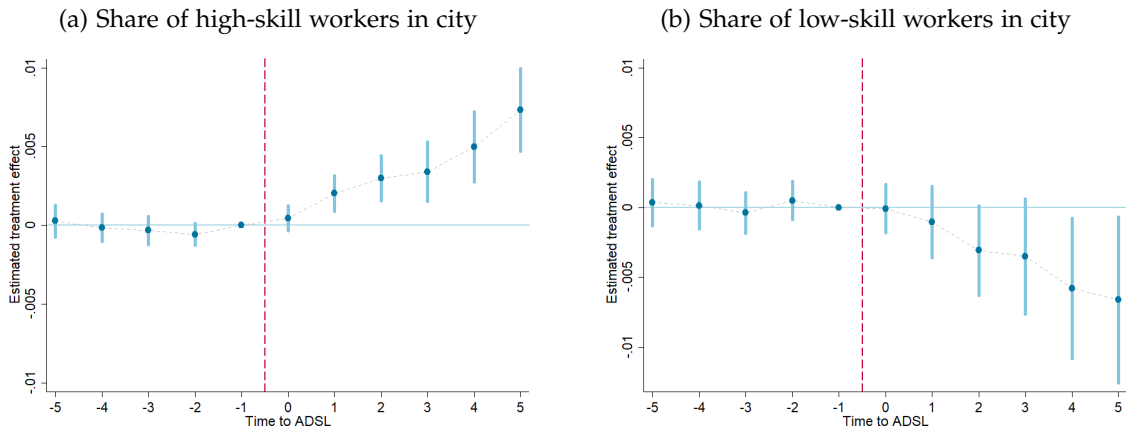
Skill-biased technical change To capture skill-biased technical change at the city level, we look at the impact of BI on two outcomes: the share of high and low-skill workers employed by firms located in the city.¹⁶

¹⁴Tables A1 and A2 in Appendix A report the summary statistics for the main outcome variables in the city level and establishment level samples, respectively.

¹⁵The positive effect of BI on labor productivity is not purely driven by an increase in the skill intensity of the firms located in the city, but goes beyond that. First, by dividing the value added of the firm by the wage bill, instead of the firm size, we partially account for the fact that high-skill workers are paid more. Second, if we include the share of high-skill workers as an additional control in the productivity regressions, the coefficients remain widely unchanged (results of these regressions are available upon request).

¹⁶All our measures of employment are expressed in terms of full-time equivalents. The occupations in the labor force are divided into high-skill workers (executive positions, managers and engineers, corresponding to the highest socio-professional category), low-skill workers (blue collar workers and and clerk, corresponding to the lowest two socio-professional categories), and others (including intermediate level professionals, foremen and technicians, which are in the middle of the socio-professional ranking). The ratio of high- and low-skill workers are thus not equal to one minus the

Figure 2: Broadband access and change in labor demand



Notes: This Figure shows regression coefficients and the the 95% confidence intervals from a dynamics event study where the dependent variable is the share of high/low-skill in a city at t and the regressors are dummies for the number of years before/after broadband access. Regression includes a set of city fixed effects as well as department-year fixed effects and control for the share of manufacturing sectors and the logarithm of the population density in 1990 interacted with a time dummy. Sample only include cities of more than 500 inhabitants in 1999. Standard errors are clustered at the department level.

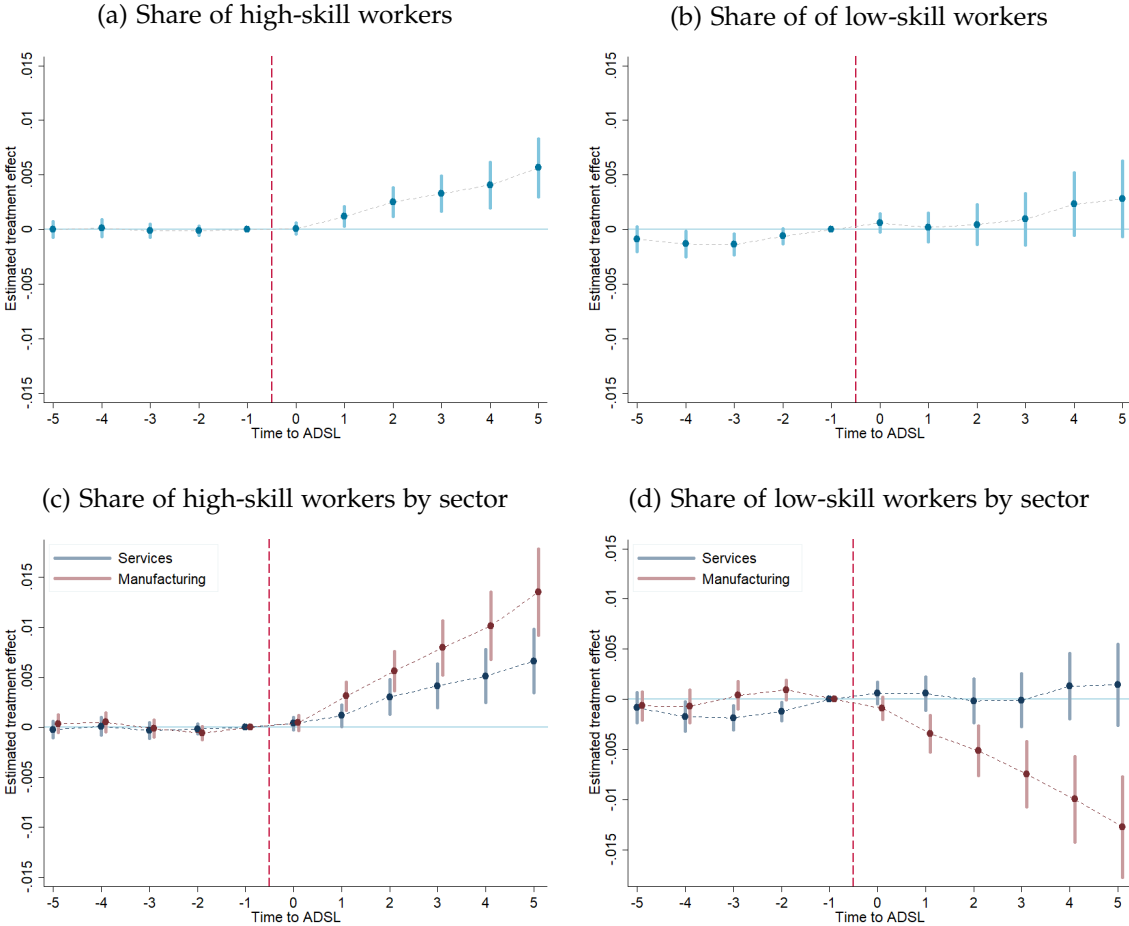
Results are presented in Figure 2(a) for the share of high skill workers and in Figure 2(b) for the share of low skill workers. Before the arrival of BI, the share of high and low skill workers evolved comparably across cities belonging to different cohorts of ADSL diffusion, conditional on department-specific time trends and the other controls. The parallel trends are a validation of our identification strategy. When cities get access to BI, they experience a general upskilling of their labor force relative to other municipalities. In particular, the share of full-time employment accounted for by the top socio-professional category increases, while the opposite happens for the bottom socio-professional category. This is in line with the thesis of skill biased technical change. To gauge the magnitude of the effect of BI on these shares, we report the relevant regression coefficients in Table A5 in Appendix A. Columns (1) and (2) show that on average, the share of high skill workers in a city increases by 0.4 percentage points following the diffusion of BI, while the share of low-skill workers decreases by 0.34 percentage points. These effects can be compared with the average share of high and low skill workers observed in cities at the beginning of the period: 6% and 79% respectively. The share of high skill workers thus increases by about 6.5% after the arrival of BI with respect to the baseline, while the share of low skill workers decreases by about 0.5%.

Such results could arise for two reasons: either because BI fosters the entry of new establishments with an average skill level that is larger than the incumbents', or be-

other, since there is one omitted category.

cause the average establishment already present in the city increases its share of high skill workers. To capture the extent to which composition effects play a role, we compare our city level results with similar event studies at the establishment level, which keep in the sample only the plants already present in the city before the arrival of the ADSL.¹⁷ Figure 3 reports the corresponding event studies.

Figure 3: Establishments’ occupational structure and broad band access



Notes: This Figure shows regression coefficients and 95% confidence intervals from a dynamic event study where the dependent variable is the share of high/low collars in an establishment at t and the regressors are dummies for the number of years before/after broadband access. Regressions follow the specification reported in equation 3. Panel (a) and (b) report the effects for all establishments, while panel (c) and (d) distinguishes between the effect for the sample of establishments in the service sector and in the manufacturing sector.

For high skill workers (Figure 3(a)), the results within establishment are qualitatively similar to the ones at the city level. This suggests that the increase in share of skilled workers shown in Figure 2 is not (only) driven by a composition effect but it is also

¹⁷The model is the same as in equation (3) but with establishment fixed effects instead of city fixed effects, and with the share of different workers’ types computed at the establishment level. These results can be interpreted as the pure within-firm effect that excludes any changes due to composition.

a phenomenon taking place within existing firms. On the contrary, the share of low skill workers does not show any change in trend in existing firms following the arrival of the ADSL (Figure 3(b)). Regression coefficients are again presented in Table A5 in Appendix A (respectively in columns (3) and (6)). The coefficients suggest that the increase in the share of high skill workers within existing firms amount to 0.6 percentage points after 5 years following the shock (6% growth with respect to baseline). The regressions at the firm level show interesting heterogeneity by broad sector. Figures 3(c) and 3(d) show the event study graphs obtained from regressions splitting the sample of establishments between manufacturing and service sectors. While the effect observed for the full sample is true both in the service and manufacturing sectors regarding high skill workers, we observe different trends in the case of low skill workers. Namely, BI is associated with a reduction in the share of low skill workers in the average manufacturing establishment, while it does not affect the average service establishment.¹⁸ This result could suggest that some low-skilled workers were displaced from one establishment to another in the same city, and in particular to establishments in the service sector.

3.2 At the individual level

In this subsection, we show that the evidence of increasing demand for skilled workers translates into an increase in wage, using our individual panel. As explained in Section 2, our data allow us to follow part of the workers over time. More precisely, we can follow every worker born in October of an even year (roughly 1/24 of the population) between 1994 and 2010. With these data, we can look at the individual wage effect of BI expansion, i.e., we can consider change in hourly wage that follows the connection of a the worker's city to the ADSL. We therefore estimate the following model:

$$\log(w_{i,t}) = \beta \tilde{Z}_{c(i),t} + X\gamma + \psi_{k,t} + v_i + \zeta_{s(i)} + \varepsilon_{i,t}, \quad (4)$$

where $w_{i,t}$ is the hourly wage of individual i over year t on average. $\tilde{Z}_{c(i),t}$ is the variable that captures the share of the city $c(i)$, where individual i works, that is connected to BI. To some reasonable extent, \tilde{Z} can be seen as a dummy variable indicating whether the city has been connected to BI prior to year t .¹⁹ X is a vector

¹⁸Corresponding coefficients are presented in Table A5 in Appendix A.

¹⁹We show robustness to replacing \tilde{Z} by the corresponding binary variable C in Appendix Table A6.

of time-varying individual characteristics: age, age squared, an indicator of whether the job is part-time (as opposed to full-time) and gender. Finally, $\psi_{k,t}$, ν_i , $\zeta_{s(i)}$ are a set of labor market area k times year t fixed effects, individual fixed effects and sector $s(i)$ fixed effects. ε is an idiosyncratic error that we assume can be correlated within labor market areas but not across. Finally, β captures the effect (in percentage points) of being connected to BI on wage, controlling for observable and time-varying unobservable worker characteristics.

Table 2: EFFECT OF ADSL ON INDIVIDUAL WAGE

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All workers		3 skills		2 skills	
Connected	0.030*** (0.003)	0.006*** (0.001)	0.013*** (0.004)	-0.016*** (0.003)	0.010* (0.005)	-0.014*** (0.003)
× High-Skilled			0.042*** (0.013)	0.116*** (0.007)	0.052*** (0.015)	0.116*** (0.009)
× Int-Skilled			0.004 (0.004)	0.025*** (0.003)		
Age	0.032*** (0.003)	0.044*** (0.006)	0.026*** (0.002)	0.041*** (0.005)	0.020*** (0.001)	0.035*** (0.003)
Age Sq.	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Gender	0.106*** (0.004)		0.123*** (0.007)		0.125*** (0.002)	
Short Time	-0.043*** (0.009)	0.035*** (0.001)	-0.020*** (0.004)	0.035*** (0.001)	0.001 (0.005)	0.059*** (0.002)
High Skill			0.649*** (0.005)	0.210*** (0.005)	0.644*** (0.008)	0.337** (0.007)
Int. skill			0.168*** (0.003)	0.039*** (0.002)		
Initial wage (log)	0.346*** (0.025)		0.334*** (0.016)		0.249*** (0.020)	
Fixed Effects						
LMA × year	✓	✓	✓	✓	✓	✓
Sector	✓	✓	✓	✓	✓	✓
Individual		✓		✓		✓
Obs.	7,810,286	7,808,176	7,810,286	7,808,176	4,316,357	4,256,281
R Sq.	0.46	0.78	0.62	0.79	0.70	0.85

Notes: This Table shows regression results from an estimation of equation (4). Variable description is given in Table A3 of the Online Appendix A. All workers are included in the regressions, except in column (5) and (6) in which we drop intermediate skill workers. All regressions include a labor market area (*zone d'emploi*) times year fixed effect as well as a sector fixed effect at the 2 digit level. Columns (2), (4) and (6) also include an individual fixed effect. Heteroskedasticity robust standard errors clustered at the labor market area level under parenthesis.

Table 2 presents our results. Column (1) includes all workers (around 11 millions) and shows that the coefficient of the dummy variable $C_{c(i),t}$ (first line, labeled “connected”) is positive and significant. Its magnitude suggests that wage per hours permanently increase by 3% on average for all workers once connected to BI. In this specification, we did not include individual fixed effects ν_i but control for initial wage to capture the

level of skill of the worker.²⁰ Including an individual fixed effect would better control for unobserved worker heterogeneity (which includes education) and this is what we do in column (2). Our coefficient of interest remains positive and significant but somehow lower (0.6%). Columns (3) and (4) produce the same type of regression than [Akerman et al. \(2015\)](#) where we interact $C_{c(i),t}$ with a dummy variable for each skill level. In line with their results, we do see that the effect of BI on wage is significantly larger for high skill workers than for others. Columns (5) and (6) confirm these results by restricting to only low and high skill workers (i.e. excluding intermediate skill workers from the sample).²¹

Overall, these results confirm what we reported at the city level: BI is associated with a larger demand for high skill workers and this translates into higher wage, even controlling for unobserved heterogeneity and the usual controls. These results also show that the increasing demand for high skill workers observed at the city and establishment level is not a pure composition effect as overall, the arrival of BI benefits more this class of workers.

4 BI Expansion and Outsourcing

We have seen that BI acts as a general purpose technology. Once connected, firms become more productive and tend to hire more high skill workers and pay higher wage. In this section, we look more in details at the distribution of workers across firms following the arrival of BI in the city where they work, with the aim of capturing the effect of this technology on domestic outsourcing. For the sake of our analysis of domestic outsourcing, we start by defining outsourcing sectors and outsourceable occupations as follows, consistent with [Goldschmidt and Schmieder \(2017\)](#):

Definition 2.

- **Outsourceable occupations.** *Non-core occupations likely to be outsourced, offshored or subcontracted, e.g. cleaners and IT specialists.*

²⁰Initial wage is defined as the logarithm of wage per hour taken in the first year in which the worker appears in the panel, this year is then removed from the regression.

²¹Our results are stable when we consider a stricter definition of low-skill occupations (excluding clerks and administrative employees and leaving only manual workers), as shown in Table [A6](#) in Appendix.

- **Outsourcing sectors.** *Administrative and business support service sectors. High-skill outsourcing sectors: IT, accounting and consulting sectors. Low-skill outsourcing sectors: Cleaning, security, food and driving services.*

We start by showing that two emblematic "outsourcable" occupations - cleaners and IT specialists - become increasingly concentrated in firms specializing in these services after the city gets connected. More generally, we show that the degree of occupational segregation across establishments increases substantially after the arrival of the internet. Finally, we show that the average worker sees an increase in its probability to change establishment once treated, and that this effect is stronger for mobility towards outsourcing sectors, both in low skilled services (typically cleaning, driving, guarding...) and in high skilled services (accounting and IT). We view these findings as evidence that firms react to the BI shock by outsourcing some non-core occupations. The theory of skill-biased technical change states that technology substitutes some workers while it increases the demand for high-skill workers, but it does not speak directly about workers' reshuffling across and within firms. Differently from the previous waves of technological change, such as the diffusion of robots and computers, BI is not so much playing the role of replacing some specific skills, but rather is expanding the possibilities for "long-distance" interactions. These new opportunities are likely to increase the number of transactions taking place between firms, and might also affect the optimal boundaries of each business. With better information and communication, it may become easier for large firms to subcontract non-core activities to local service providers and to keep in house only the jobs with the largest added value.

4.1 At the city level

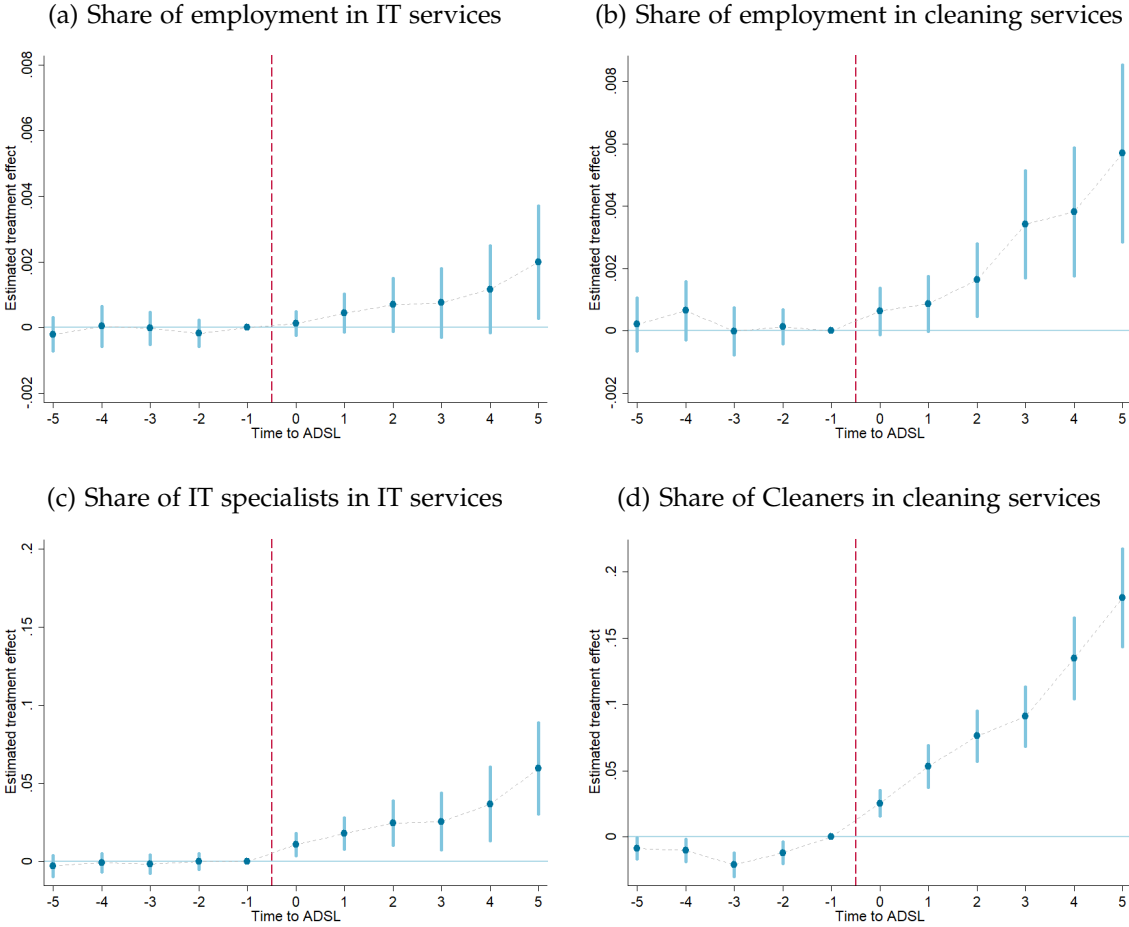
We start by looking at the causal effect of BI on outsourcing at the city level. In this subsection, we will focus on one illustrative category of outsourcable low-skill labor – cleaners – and one illustrative outsourcable high skill occupation – IT specialists.²² We consider two main measures of outsourcing at the city level, which are computed separately for the high- and low-skill segments: i) the share of total employment in

²²We decide to focus on cleaners and IT specialists because these occupations are well-identified into one single four-digit category in the French occupational nomenclature, and their corresponding service sectors - IT services and cleaning services, are also well identified in the classification of activities.

the city concentrated within outsourcing sectors, and ii) the share of “outsourcable” workers in the city that are employed in outsourcing sectors.²³

While the first is a measure of demand for IT and cleaning services that might react even in the absence of an increase in outsourcing, the second captures the change in the concentration of outsourcable workers within their respective services regardless of the total volume change. All measures are computed using a measure of employment in full-time equivalent.

Figure 4: Effect of ADSL on high- and low-skill outsourcing



Notes: This Figure shows regression coefficients and 95% confidence intervals from a dynamic event study where the dependent variables are the share of workers employed in IT services (cleaning services) in a city at t (Figures 4(a) and 4(b)) and the share of IT specialists (cleaners) working in IT services (cleaning services) in a city at t (Figures 4(c) and 4(d)). The regressors are dummies for the number of years before/after broadband access. Regression includes a set of city fixed effects as well as department-year fixed effects and control for the share of manufacturing sectors and the population density in 1990 interacted with a time dummy. Sample only include cities of more than 500 inhabitants in 1999. Standard errors are clustered at the department level.

Figure 4 reports the event study graphs of the two main outcomes, separately in the

²³Outsourcing sectors refer to the IT and cleaning services respectively, while the outsourcable occupations are IT specialists and cleaners. See Appendix B for a formal definition.

case of high- and low-skill outsourcing.²⁴ We see that the share of employment in IT services increases slightly after the arrival of the ADSL, while the share of IT specialists employed in IT services grows substantially right after the city gets connected. We can thus imagine that IT specialists are mostly outsourced towards establishments that were already present in the territory, at least at the beginning of ADSL connection. In the low-skill segment, we observe a very striking increase in the share of employment concentrated within cleaning services after the arrival of the ADSL, and the same is true for the share of cleaners that are employed directly by firms in this specialized sector.

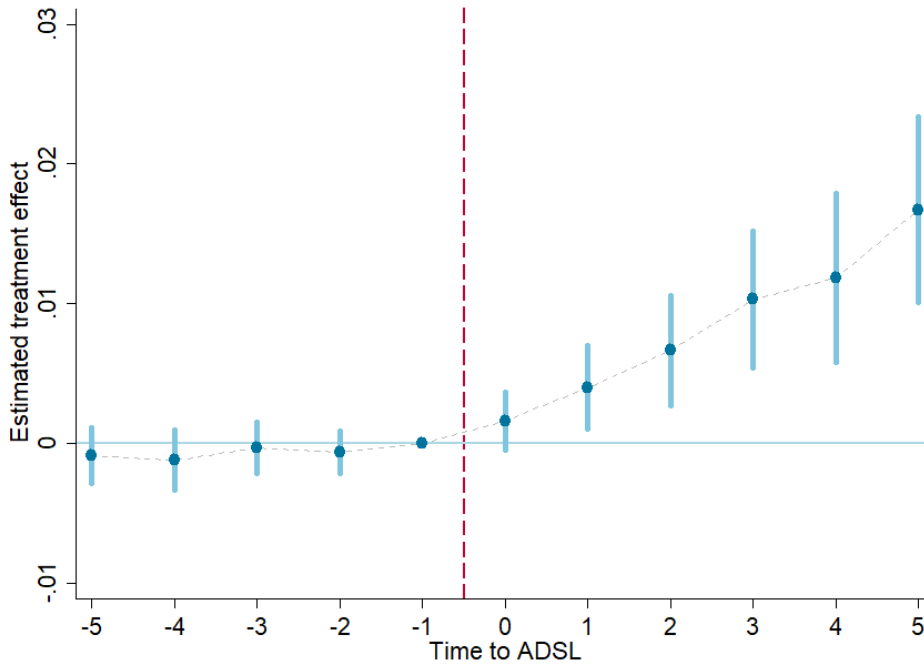
While the magnitude of the coefficients might appear small, the effect is actually far from trivial when compared to the baseline (pre-treatment) values. The share of city employment accounted for by IT services was about 0.1% at the beginning of the period, such that the average impact of ADSL arrival in the 5 years after adoption constitutes a growth of 90% (i.e. the employment in this sector almost doubles). Cleaning services accounted for about 0.2% of total city employment in 1997, and the effect of BI connection is a growth of 138% (the employment in this sector more than doubles). When it comes to the concentration of IT specialists within their service sector, the baseline value is 9%, and the effect of the ADSL is of 2.8 additional percentage points (a growth of 30%). The share of cleaners within cleaning services was 9.5% in 1997 and it grows on average by 9.8 additional percentage points thanks to the arrival of BI (+103%). Given these magnitudes, we can infer that the arrival of the internet generated a structural change in the way these services are used by their business customers. This is a first indication that BI catalyzed the growth in domestic outsourcing, and this for non-core activities situated both at the low- and high-skill end of the spectrum.

In what precedes, we focused on two emblematic examples of outsourceable occupations that are easily identifiable in the data. We now provide a more general and reduced-form evidence of the effect of BI had on the occupational specialization of firms. In fact, the increased probability of outsourcing non-core activities is expected to exacerbate the segregation of workers into establishments that mostly employ their type. To test this phenomenon, we run the same specification reported in equation 3 on a measure of occupation sorting across firms. We measure the latter by computing an Herfindahl–Hirschman Index for the concentration of employment across occupations within each establishment, and by taking the weighted average for each

²⁴Table A7 in Appendix A shows the corresponding regression coefficients.

city.²⁵ Figure 5 presents the event study graph for the effect of ADSL arrival on the occupational concentration of establishments. Once again, municipalities belonging to different cohorts of broadband expansion followed very similar trends before the arrival of the internet, while after connection they become increasingly sorted. This indicates that, after the arrival of BI, establishments within the city specialize by employing fewer types of occupations such that workers become increasingly segregated into firms that primarily hire their type.

Figure 5: Concentration of occupations within establishments



Notes: This Figure shows regression coefficients and the 95% confidence intervals from a dynamics event study where the dependent variable is the weighted average of occupational concentration within establishments (measured with HHI) located in a city at t and the regressors are dummies for the number of years before/after broadband access. The specification follows equation 3.

Table A8 in Appendix A quantifies the effect at the city level by presenting the dynamic post-BI coefficients (column 1), and shows the effect obtained from regressions at the establishment level, both overall (column 2) and separately for services and manufacturing (columns 3 and 4). We also report results from running an analog

²⁵The concentration of occupations within each establishment i is computed with the following formula: $HHI_i = \sum_{o=1}^{18} s_{oi}^2$, where o are the 18 occupational categories that compose the French private sector, and s_{oi} is the share of the total hours worked in the establishment performed by people employed in a given occupation. At the city level c , we compute the average establishment concentration as following: $HHI_c = \sum_{i=1}^N \omega_{ic} HHI_{ic}$, where ω_{ic} is the share of total number of hours worked in the city accounted for by each establishment i .

model but at the establishment level in Figure A2 in Appendix A. After five years following the arrival of the ADSL connection in the city, we observe an average increase in the occupational concentration of about 0.016 (+4% relative to baseline). This is confirmed by the regressions at the establishment level, hinting that the effect is not (only) driven by changes in composition but that it takes place even within existing plants located in the municipality. When we split the effect by broad sectors, we see that the entirety of it is driven by an increase in occupational concentration within service firms (+0.013 points HHI after 5 years, equivalent to a 3% growth relative to baseline). These results suggest that the arrival of broadband internet significantly impacted the distribution of occupations within establishments by shifting the optimal boundaries of the firm.

However, in this analysis we do not capture workers flows in and out of firms. We can thus not see directly whether the same individuals are outsourced out of their former firms towards the outsourcing sectors.

4.2 At the individual level

In this section, we leverage our panel data to follow the workers over time and study their mobility decisions. More precisely, we look at the effect of BI expansion on worker’s probability to change job. We consider different type of mobility: within/between the same city or labor market area (“Zone d’Emploi”) and/or from an establishment outside the outsourcing sector to an establishment in the outsourcing sector.

We therefore estimate the following linear probability model:

$$Move_{i,t} = \beta \tilde{Z}_{c(i),t} + X\gamma + \psi_{k,t} + v_i + \zeta_{s(i)} + \varepsilon_{i,t}, \quad (5)$$

where $Move_{i,t}$ is a binary variable equal to 1 if the worker i has moved on year t and 0 otherwise.²⁶ \tilde{Z} has been defined above and measures the exposition to BI. X is a vector of standard time-varying individual characteristics usually included in wage regressions: age, age squared, an indicator of whether the job is part-time (as opposed to full-time). Finally, $\psi_{k,t}$, v_i , $\zeta_{s(i)}$ are a set of labor market area k times year t fixed effects, individual fixed effects and sector $s(i)$ fixed effects. ε is an idiosyncratic

²⁶Specifically, we set this dependent variable to 1 in year t if a worker is not in the same establishment in year $t + 2$ when compared to year t . This is because workers sometimes disappear from the sample the year immediately following a mobility.

error that we assume can be correlated within labor market areas but not across. β captures the effect of being connected to BI on the probability of moving, controlling for observable and time-varying unobservable worker characteristics.

Table 3: EFFECT OF ADSL ON WORKERS' MOBILITY

	High-skill workers			Low-skill workers		
	(1) Any move	(2) To outsourcing	(3) Other	(4) Any move	(5) To outsourcing	(6) Other
Mobility						
Any	0.063*** (0.020)	0.177** (0.081)	0.066*** (0.022)	0.070*** (0.012)	0.086* (0.046)	0.064*** (0.013)
Same city	-0.013 (0.097)	-0.189 (0.138)	-0.004 (0.100)	0.257*** (0.040)	0.367*** (0.115)	0.262*** (0.043)
Same LMA	-0.004 (0.038)	0.062 (0.084)	0.020 (0.033)	0.129*** (0.017)	0.164** (0.066)	0.130*** (0.017)
Different city	0.102** (0.048)	0.314*** (0.097)	0.096 (0.067)	-0.021 (0.018)	0.033 (0.046)	-0.015 (0.019)
Different LMA	0.174*** (0.054)	0.328** (0.130)	0.132** (0.053)	-0.040* (0.022)	-0.003 (0.058)	-0.036 (0.024)
Fixed Effects						
LMA \times year	✓	✓	✓	✓	✓	✓
Sector	✓	✓	✓	✓	✓	✓
Obs.	1,054,063	1,054,063	1,054,063	5,143,010	5,143,010	5,143,010

Notes: This Table presents the point estimate and standard errors of coefficient β in equation (5). The dependent variable is a binary variable equal to 1 if worker i has changed establishment between t and $t + 2$. Each line conditions on different type of mobility (any move, within/between city and within/between labor market area - *Zone d'emploi*). Columns (1) and (4) consider any move, columns (2) and (5) consider mobility to a firm in the outsourcing sector and columns (3) and (6) consider mobility to firms excluding the outsourcing sectors. The outsourcing sectors respectively denote the high-skill outsourcing sectors in column (2) (e.g. IT services) and the low-skill outsourcing sectors in column (5) (e.g. cleaning services). The dependent variable has been standardized by its sample mean. Columns (1), (2) and (3) restrict to high-skilled occupation workers and columns (4), (5) and (6) to low-skilled occupation workers. OLS estimator with standard errors clustered at the LMA level and robust to heteroskedasticity. Time period: 1995-2008.

Table 3 presents our results. We report coefficient β from equation (5) for different types of mobility. Columns 1 to 3 restrict to high-skill workers. In column 1, the dependent variable is equal to 1 in a case of a mobility, regardless of the sector of the destination firm. Column 2 conditions on moving to a firm in any of the high-skill outsourcing sector (IT, Accounting etc..) and column 3 conditions on moving to a firm outside these outsourcing sectors. Columns 4 to 6 do the same but for low-skill workers, and for the corresponding outsourcing sectors (cleaning, driving, security etc..). Each line then consider different types of mobility: within city, within labor market area (*Zone d'emploi*), between city and between labor market area. We have standardized the dependent variable by its sample mean for each regression. Hence the coefficient should be interpreted as a deviation in percentage point from the average probability of moving.

These result show that being connected to BI is associated with a greater propensity to move, both for high and low skill workers with a larger relative effect for mobility to an outsourcing sector. Yet, the pattern of mobility are different across skill groups. Low-skill workers tend to move locally while high skilled workers are more mobile

and can move across different labor market areas.

4.3 Discussion

The results presented in this section suggest that BI accelerated the outsourcing of some high and low skilled occupations. Regarding low skilled workers, the set of occupations that are outsourced correspond to occupations that are usually considered "non-core". These occupations are typically associated with a lower degree of complementarity with the firm's other assets (see [Aghion et al., 2019a](#)). In order to understand the mechanisms by which firms select the low-skilled workers to be outsourced, we develop a theoretical model in Appendix D. The model rationalizes how a productivity shock leads firm to outsource low skilled occupations that are less complementary. In this theoretical framework, firms are modeled as an aggregate of different occupations that are performed by workers. They consider their current level of productivity and choose the optimal level of human capital to allocate to each occupation, taken into account the fact that there is a cost associated with the formation of such human capital. Such cost can be seen as a pure training cost or a cost of monitoring and managing low skilled tasks. Alternatively, firms can choose to outsource some occupations. In doing so, they are exempt of training cost but the worker only has a minimal level of firm specific human capital. If firms are constrained in the resource they can dedicate to training and supervising workers, then an increase of productivity (for example following BI) would lead firms to outsource their low skilled occupations workers. Still some low skilled occupations remain valued by firms which will choose to dedicate all their resource to raise their level of firm-specific human capital.²⁷

This simple theoretical framework can therefore explain why BI accelerates the outsourcing of some low skilled occupations such as cleaners. But what about high skill workers like IT specialists that also seem to be more largely outsourced following BI expansion? We have already seen that mobility pattern of these occupations is different with less local moves. This is consistent with the view that, in addition to generating productivity gains in treated firms, BI also decrease the communication costs which triggered important job reorganization within and between firms, including for high skill occupation workers.²⁸ The high skilled occupations that are typically

²⁷This finding is consistent with [Aghion et al. \(2019a\)](#) who finds that some low skilled occupation workers (typically these with large soft-skills) benefit from technological progress.

²⁸[Charnoz et al. \(2018\)](#) study the effect of the French High-speed Rail to study the impact of a reduction

outsourced, IT specialists and accountants, are occupations which are in high demand and that would benefit from being concentrated in specialized establishments and to be contracted.

Therefore, it suggest that low-skilled outsourcing is a selection mechanism imposed to low-skilled workers that are less complementary to the firm other assets. On the contrary, outsourcing of high skilled occupation could benefit high-skilled workers, as they are able to capture part of the increasing profit of firms from a cost reduction.²⁹ These different mechanisms should have a opposite impact on the wages of low- and high-skilled outsourced workers. In next section, we look at the dynamic of wage following outsourcing event both for the outsourced workers and for incumbent workers that remain employed.

5 Effect of outsourcing on wages

Our findings suggest that BI shocked the labor market in significantly and impacted the wage of workers. Importantly for this section, BI expansion also increased mobility of workers across establishments, with a particularly strong effect to the mobility toward firms in outsourcing sectors for some occupations. To the extent that this shock can be considered exogenous, it allows us to consider *individual* outsourcing events, defined as follows:

Definition 3.

- *Individual outsourcing event.* The mobility of at least one worker from a firm outside the outsourcing sector to a firm belonging to the outsourcing sector

This definition allows us to capture many outsourcing events, respectively for high- and low- skill workers. We thus look in more details at the wage dynamics of workers around these events respectively for the outsourced workers (what we call “direct effect”) and for workers that remain employed in the firm (“indirect effect”).

in communication costs and show how this generated important reorganization within firms with more specialized establishments.

²⁹Note that in the model, non outsourced low-skilled workers also capture part of the surplus from outsourcing.

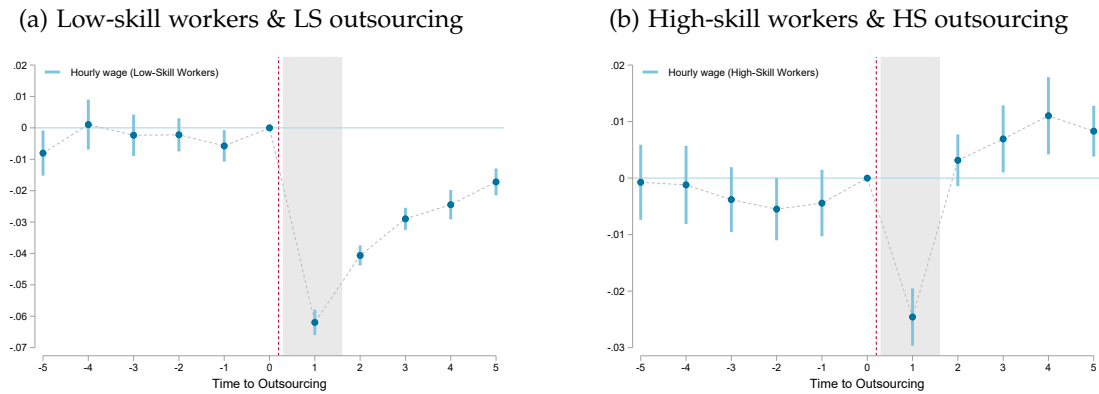
5.1 Direct effect

To test the direct effect, we leverage our individual panel data and follow outsourced workers before and after an individual outsourcing event. We restrict to the subset of workers that experience one and only one outsourcing event over the period of observation which allows us to define our event study. We then look at the evolution of their hourly wage by estimating the following dynamic model:

$$\log(w_{it}^{ow}) = \sum_{\tau=-v}^{v'} \alpha_{\tau} \mathbb{1}\{t = t_i + \tau\} + X\gamma + \psi_{k,t} + \nu_i + \zeta_{s(i)} + \varepsilon_{i,t} \quad (6)$$

where w_{it}^{ow} represents the hourly wage of workers that are being outsourced by their firms, and t_i is the year of the event. Just like in equation (4), X is a vector of time-varying individual characteristics: age, age squared and an indicator of whether the job is part-time and $\psi_{k,t}$, ν_i , $\zeta_{s(i)}$ are a set of labor market area k times year t fixed effects, individual fixed effects and sector $s(i)$ fixed effects. ε is an idiosyncratic error that we assume can be correlated within labor market areas but not across. We estimate this regression separately for low skill workers and high skill workers. The sample respectively include 16,271 and 8,530 different workers.

Figure 6: Wage of outsourced workers before and after the outsourcing event



Notes: This Figure shows regression coefficients and confidence intervals at ± 2 standard errors from a dynamics event study where the dependent variables are the log hourly wage of workers being outsourced from the establishment at time t , and the regressors are dummies for the number of years before/after the establishment experiences an outsourcing event as well as control variables: age, age squared, short-time dummy and a set of year times labor market area and individual fixed effects. Shaded area denotes the year of the mobility which is associated with noisy measures of work duration. Left-hand side panel restrict to low skill outsourcing (16,271 workers) and right-hand side to high skill outsourcing (8,530 workers). Standard errors are computed using a heteroskedastic robust variance covariance estimators allowing for autocorrelation at the establishment level.

Figure 6 shows that the hourly wage of outsourced low-skill workers sharply decreases after the outsourcing event. This finding is in line with results evidenced by [Goldschmidt and Schmieder \(2017\)](#), which explain this phenomenon by the fact that firms in the outsourcing sectors benefit from lower rents, on average, than other

companies. This translates into lower wage premia for their employees.³⁰ We find an average effect that ranges from -4%, right after the outsourcing event to -2% five years after, gradually converging toward the pre-treatment level. On the contrary, outsourced high-skill workers enjoy a small but significant gain in hourly wage in the long run after the outsourcing transition (+1% five years after the event), a pattern which is consistent with broadband stimulating demand for IT services thus resulting in an increase of IT workers outside options and voluntary job to job transitions. These particular high skilled occupations indeed continue to be in high demand and can easily be contracted, especially as communication technologies improve. By regrouping these occupations, specialized firms can serve different clients and generate more profit first by maximizing the utilisation rate of their inputs (mainly labour) and second by reducing the fixed costs. This mechanism is somehow similar to some low skilled outsourcing, but in the case of IT workers or Accountants, the outsourced workers have a larger bargaining power and can capture part of the rent by commanding a higher wage.

Overall, those results emphasizes an heterogeneous impact of outsourcing on worker's wage. While low skill workers suffer from a significant wage loss, high-skill workers seem to benefit from outsourcing, as they are able to capture part of the increasing profit of firms from a cost reduction.

5.2 Indirect effect

Finally, in this last part of the analysis we provide suggestive evidence of what are the consequences of outsourcing for the salary of the workers that remain employed by the original plant. For the limited sub-period going from 2002 to 2007, we can define the individual outsourcing events at the establishment level as the data makes it possible to follow workers over two consecutive years, but only over this short period of time. An establishment is considered to be outsourcing high-skill activities if at least one of his executives moves towards the high-skill outsourcing sector in a given year. Similarly, an establishment is considered to be outsourcing low-skill activities if at least one of its low-skill workers moves towards the low-skill outsourcing sector

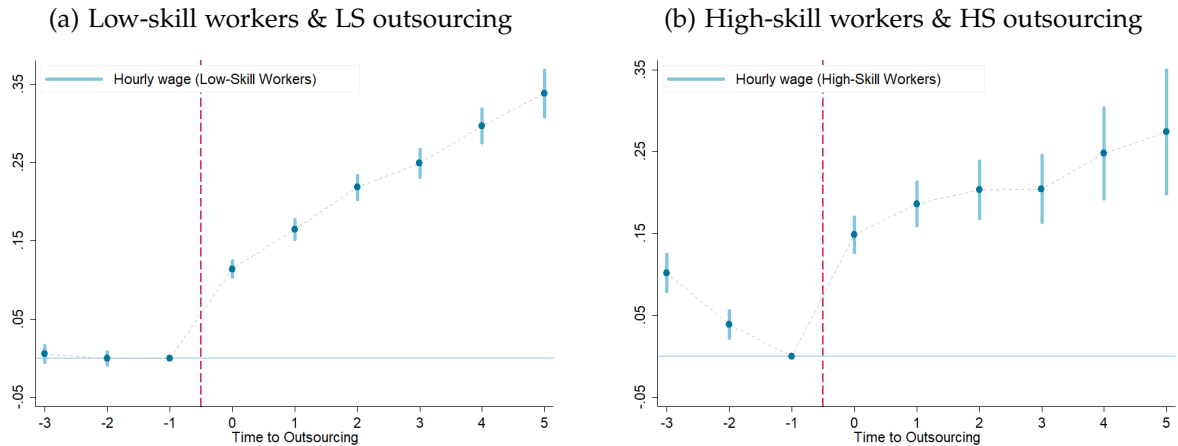
³⁰The shaded area corresponds to the year of the move, when the outsourced worker quit its previous employer to join an outsourcing firm. This transition period is known to create reporting errors of the number of hours worked in the data, resulting in an outlier estimate for the dummy +1. In consequence, we focus on the coefficient from +2 to +5 in our analysis.

in a given year.³¹ In this section, we consider the effect of an outsourcing event on the average wage of high- and low-skill workers that remain within the original firm. This complements the analysis on the impact of outsourcing on the wage of outsourced workers. We run the following simple event study model:

$$\log(w_{ft}^{ow}) = \sum_{\tau=-v}^{v'} \alpha_{\tau} \mathbb{1}\{t = t_f + \tau\} + \pi_f + \varepsilon_{f,t} \quad (7)$$

where w_{ft}^{ow} represents the average hourly wage of workers in outsourceable occupations that are still employed in the original establishment, and t_f is the year of the outsourcing event for establishment f . The regression further controls for establishment fixed effects (π_f). This model compares the change in compensation observed before and after the outsourcing event with the trends displayed by firms that outsource later in time. We take this results as suggestive evidence, since we cannot rule out the fact that outsourcing plants might take their decision endogenously to their performance.

Figure 7: Wage of incumbent workers before and after the outsourcing event



Notes: This Figure shows regression coefficients and confidence intervals at ± 2 standard errors from a dynamics event study where the dependent variables are the log hourly wage of workers remaining in the establishment at time t , and the regressors are dummies for the number of years before/after the establishment experiences an outsourcing event. High-skill outsourcing events at the establishment level are defined as the movement of at least one executive out of the estab. and towards a high-skill service sector (IT services or accounting). Low-skill outsourcing events are defined as the movement of at least one low-skill worker out of the estab. and towards a low-skill service sector (cleaning services, food services, security services or driving services). Regression includes a set of establishment fixed effects as well as year fixed effects. Sample only include the period going from 2002 to 2007 because the event cannot be defined on earlier data. Standard errors are computed using an heteroskedastic robust variance covariance estimators allowing for autocorrelation at the establishment level.

Figure 7 shows that the wage of incumbent workers jumps up right at the time of

³¹We test robustness of the results to defining the event as "at least 10% or 20% of technical / unskilled workers moves to the respective sector" and we find the same outcome (results available upon request).

outsourcing. The magnitude of the change is similar for the wage of the remaining low-skill workers - where the event is outsourcing towards low-skill services -, and the wage of the remaining high-skill workers - where the event is outsourcing towards high-skill services. This effect is likely to be due to a composition change within the plant: the firms generally outsource the workers that were paid the least within their category. This might be linked to the fact that they were not involved in the core activities of the plant, and are less complementary to the firm's other productive assets (as predicted by the model in Appendix D). The positive trend displayed by the salaries of incumbents, both low and high skill, is an indication that firms increase the compensation of the remaining workers. Table A9 in Appendix reports the coefficients corresponding to Figure 7 and further shows that the occupational concentration within establishments increases after an outsourcing event, both for high- and low-skill outsourcing. This is an additional confirmation that firms take advantage of the new communication opportunities to outsource tasks at the periphery of their core activities and only keep in-house the workers with the greatest added value. Finally, Figure A3 show that a similar picture arises when we restrict high-skill outsourcing to movements of executives towards the IT service sector and low-skill outsourcing to movements of low-skill workers towards the cleaning service sector.

6 Conclusion

The diffusion of the internet has fostered many changes in the way firms operate, some of which differ from what observed in the previous waves of technological change. In particular, this technology enabled better long-distance communication and information sharing, and is thus likely to have affected the optimal boundaries of the firm. In this paper we examine the role that broadband internet played in incentivizing firms to outsource some activities, both in the high- and low-skill segment, and we describe its consequences on the affected workers. We leverage the staggered roll-out of broadband connection across the French territory to adopt an event study design. The latter compares similarly dense municipalities within a given department that gain access to BI at different points in time. Our results show that the internet is not only skill-biased, but also increases the degree of occupational concentration within establishments by pushing firms to outsource activities with lower degrees of complementarity in production. This phenomenon touches both low-skill occupations such as cleaning, and high skill occupations such as IT. Finally, we provide suggestive evidence that high-skill workers experience wage gains through outsourcing, while

low-skill workers experience wage losses. These findings confirm that the impact of the internet technology is not homogeneous across the skill distribution, and unveil that domestic outsourcing is as an additional mechanism through which this effect plays out. More broadly, it appears that these forces contribute to increase the segregation of workers in the labor market of advanced countries, which might have detrimental effects on the level of trust and cohesion of our societies.

Appendix

Outline

- Appendix **A** presents additional empirical results
- Appendix **B** presents the data in more details
- Appendix **C** presents the roll-out of broadband internet in France
- Appendix **D** presents the theoretical framework

A Additional Results

A.1 Tables

Table A1: Variable description for city-level regressions

VARIABLES	All sample mn/(sd)	By cohort of ADSL arrival		
		99-01 mn/(sd)	02-04 mn/(sd)	05-07 mn/(sd)
N. high skill workers	82.8 (763.7)	279.1 (1458.8)	12.6 (34.0)	9.2 (49.3)
Share high skill workers	0.07 (0.07)	0.09 (0.08)	0.06 (0.06)	0.05 (0.06)
N. low skill workers	356.1 (1361.9)	1001.9 (2480.3)	137.8 (236.9)	92.4 (357.8)
Share low skill workers	0.80 (0.15)	0.74 (0.15)	0.81 (0.14)	0.83 (0.15)
Occupational concentration (HHI)	0.42 (0.16)	0.40 (0.12)	0.42 (0.16)	0.44 (0.19)
Value added per salary mass (2010 euros)	2.01 (1.99)	2.01 (1.05)	2.00 (1.58)	2.03 (3.07)
Share of empl. in IT services	0.005 (0.04)	0.011 (0.05)	0.002 (0.04)	0.002 (0.04)
Share of IT specialists in IT services	0.10 (0.26)	0.15 (0.30)	0.04 (0.18)	0.04 (0.17)
Share of empl.t in cleaning services	0.011 (0.08)	0.019 (0.08)	0.009 (0.08)	0.008 (0.07)
Share of cleaners in cleaning services	0.18 (0.36)	0.29 (0.42)	0.06 (0.24)	0.09 (0.28)
Average establishment size	35.1 (51.5)	40.5 (52.7)	34.8 (55.5)	30.0 (41.7)
N. of establishments	12.7 (52.4)	36.3 (96.6)	4.7 (6.5)	3.2 (10.4)
Observations	116'648	57'875	21'650	37'123

Notes: Description of variables used in city-level regressions.

Table A2: Variable description for establishment-level regressions

VARIABLES	All sample mn/(sd)	By sector	
		services mn/(sd)	manufac- turing mn/(sd)
N. high skill workers	6.2 (46.2)	8.1 (52.2)	5.3 (44.2)
Share high skill workers	0.12 (0.17)	0.10 (0.13)	0.11 (0.18)
N. low skill workers	28.4 (96.0)	41.4 (138.7)	24.6 (78.3)
Share low skill workers	0.68 (0.27)	0.72 (0.22)	0.69 (0.28)
Occupational concentration (HHI)	0.41 (0.20)	0.35 (0.15)	0.43 (0.21)
Value added per salary mass (2010 euros)	2.08 (5.00)	2.00 (5.34)	2.10 (4.91)
Observations	1'871'603	1'330'080	455'410

Notes: Description of variables used in establishment-level regressions.

Table A3: Variable description for Table 2

Variable	Description	Mean	p25	p75
Log of wage	log of hourly wage (dependent variable)	2.41	2.10	2.63
Age	Age of the worker	37	28	46
Age Sq.	Age \times Age	1,507	784	2,116
Gender	Gender of the worker	0.63	0	1
Short Time	Dummy for declaring working part time	0.17	0	1
High Skill	Dummy for working in a high skill occupation	0.13	0	1
Int. Skill	Dummy for neither working in high or low skill occupation	0.45	0	1
Initial Wage (log)	Log of hourly wage taken in the first year the worker appear in the data	2.22	1.93	2.40

Notes: Variable description used in the panel data wage regression and basic descriptive statistics.

Table A4: Productivity Effects

VARIABLES	(1)	(2)	(3)	(4)
	City level	Establishment level		
	Total	Total	Services	Manuf.
T = 0	0.00621** (0.00297)	0.00383** (0.00162)	0.00153 (0.00193)	0.00523* (0.00294)
T = +1	0.0175*** (0.00398)	0.00539** (0.00227)	0.00165 (0.00246)	0.00684 (0.00428)
T = +2	0.0232*** (0.00505)	0.0106*** (0.00339)	0.00957** (0.00367)	0.00629 (0.00594)
T = +3	0.0254*** (0.00702)	0.0156*** (0.00427)	0.0170*** (0.00457)	0.00310 (0.00718)
T = +4	0.0304*** (0.00850)	0.0190*** (0.00499)	0.0224*** (0.00547)	0.00225 (0.00787)
T = +5	0.0449*** (0.00984)	0.0276*** (0.00626)	0.0336*** (0.00739)	0.00334 (0.00955)
Average effect	0.0246*** (0.00562)	0.0137*** (0.00356)	0.0143*** (0.00394)	0.00451 (0.00588)
Observations	110,431	1,143,321	776,041	316,364
R-squared	0.475	0.657	0.676	0.605

Notes: Column (1) run the regression at the city level, following equation 3, where the dependent variables is the average productivity (value added per salary mass) of establishments in the city weighted by establishment size. Only single-establishment firms are considered given that the value added data is only available at the firm level. This regression controls for the share of manufacturing employment, the population density in 1999 interacted with year dummies, department x year fixed effects and city fixed effects. Standard errors are clustered at the department level. Columns (2) to (4) run the same specification on this outcome keeping the sample at the establishment level, replacing city fixed effects by establishment fixed effects. At the establishment level, regressions are run on the full sample, on the sample of service firms only, and on the sample of manufacturing firms only.

Table A5: Effect of ADSL on city and establishment structure

VARIABLES	(1) City level		(2) Establishment level					
	Sh. of high skill workers	Sh. of low skill workers	Sh. of high skill workers			Sh. of low skill workers		
	Total	Total	Total	Services	Manuf.	Total	Services	Manuf.
T = 0	0.000806** (0.000393)	-0.000163 (0.000922)	0.000272 (0.000282)	0.000456 (0.000329)	0.000777* (0.000432)	0.000856** (0.000412)	0.00103** (0.000495)	-0.00148** (0.000609)
T = +1	0.00245*** (0.000552)	-0.00112 (0.00134)	0.00140*** (0.000477)	0.00125** (0.000561)	0.00358*** (0.000782)	0.000237 (0.000655)	0.000594 (0.000770)	-0.00423*** (0.000935)
T = +2	0.00348*** (0.000726)	-0.00317* (0.00169)	0.00296*** (0.000730)	0.00311*** (0.000913)	0.00620*** (0.00106)	0.000476 (0.000879)	-0.000169 (0.00104)	-0.00611*** (0.00125)
T = +3	0.00395*** (0.000944)	-0.00358* (0.00215)	0.00388*** (0.000920)	0.00421*** (0.00114)	0.00864*** (0.00147)	0.000705 (0.00110)	-0.000543 (0.00125)	-0.00861*** (0.00162)
T = +4	0.00562*** (0.00111)	-0.00585** (0.00263)	0.00470*** (0.00114)	0.00518*** (0.00139)	0.0109*** (0.00180)	0.00180 (0.00133)	0.000301 (0.00155)	-0.0113*** (0.00209)
T = +5	0.00803*** (0.00133)	-0.00668** (0.00316)	0.00624*** (0.00142)	0.00668*** (0.00165)	0.0145*** (0.00232)	0.00205 (0.00165)	3.27e-05 (0.00196)	-0.0142*** (0.00243)
Average effect	0.00406*** (0.000767)	-0.00343* (0.00185)	0.00324*** (0.000795)	0.00348*** (0.000959)	0.00743*** (0.00125)	0.00102 (0.000945)	0.000208 (0.00110)	-0.00766*** (0.00140)
Observations	115,962	115,962	1,683,410	1,188,348	415,857	1,683,410	1,188,348	415,857
R-squared	0.771	0.800	0.905	0.914	0.866	0.916	0.916	0.908

Notes: Columns (1) and (2) run the regression at the city level, following equation 3, where the dependent variables are the share of high- and low-skill workers out of total employment at the city level (in full-time equivalent), and controls are the share of manufacturing employment, the population density in 1999 interacted with year dummies, department x year fixed effects and city fixed effects. Standard errors are clustered at the department level. Columns (3) to (8) run the same specification on these two outcomes keeping the sample at the establishment level, replacing city fixed effects by establishment fixed effects. For each outcome, regressions are run on the full sample, on the sample of service firms only, and on the sample of manufacturing firms only.

Table A6: EFFECT OF ADSL ON INDIVIDUAL WAGE

Sample	(1)	(2)	(3)	(4)
	3 skills		2 skills	
Connected	0.015*** (0.003)	-0.006*** (0.002)	0.015*** (0.003)	-0.011*** (0.002)
Connected × High-Skilled	0.043*** (0.011)	0.099*** (0.008)	0.042*** (0.010)	0.105*** (0.007)
Connected × Int-Skilled	0.010** (0.005)	0.036*** (0.001)		
Age	0.018*** (0.001)	0.028*** (0.004)	0.021*** (0.001)	0.035*** (0.004)
Age Sq.	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Gender	0.062*** (0.001)		0.060*** (0.002)	
Short Time	-0.018*** (0.003)	0.030*** (0.000)	-0.016*** (0.002)	0.033*** (0.001)
High Skill	0.627*** (0.005)	0.345*** (0.007)	0.626*** (0.003)	0.256*** (0.004)
Int. skill	0.232*** (0.006)	0.087*** (0.001)		
Initial wage (log)		0.247*** (0.016)		0.252*** (0.013)
<u>Fixed Effects</u>				
LMA × year	✓	✓	✓	✓
Sector	✓	✓	✓	✓
Individual		✓		✓
Obs.	11,048,301	11,048,301	8,321,841	8,321,841
R Sq.	0.65	0.81	0.59	0.76

Notes: This Table replicates Table 2 with the only difference that the group of low skilled workers no include clerical occupations. See Table 2 for details and Table A3 for a definition of covariates.

Table A7: Effect of ADSL on high and low-skill outsourcing

	(1)	(2)	(3)	(4)
	IT outsourcing		Cleaning outsourcing	
	Sh. Employment in IT services	Sh. IT specialists in IT services	Sh. Employment in cleaning services	Sh. cleaners in cleaning services
T = 0	0.000177 (0.000223)	0.0106*** (0.00401)	0.000612 (0.000416)	0.0328*** (0.00565)
T = +1	0.000490 (0.000326)	0.0174*** (0.00544)	0.000905* (0.000484)	0.0599*** (0.00832)
T = +2	0.000738* (0.000431)	0.0236*** (0.00747)	0.00171*** (0.000604)	0.0818*** (0.00995)
T = +3	0.000798 (0.000540)	0.0243** (0.00962)	0.00354*** (0.000859)	0.0957*** (0.0121)
T = +4	0.00120* (0.000692)	0.0351*** (0.0123)	0.00398*** (0.00102)	0.139*** (0.0160)
T = +5	0.00203** (0.000845)	0.0575*** (0.0150)	0.00590*** (0.00143)	0.184*** (0.0193)
Average effect	0.000906* (0.000476)	0.0281*** (0.00823)	0.00277*** (0.000712)	0.0989*** (0.0110)
Observations	115,962	26,426	115,962	34,653
R-squared	0.810	0.754	0.769	0.742

Notes: The regressions are run at the city level following equation 3. All columns control for the share of manufacturing employment, the population density in 1999 interacted with year dummies, department x year fixed effects and city fixed effects. Standard errors are clustered at the department level. The outcomes capture the share of total employment in the city concentrated in IT services (column 1) and cleaning services (column 3), and the share of total IT specialists / cleaners that are employed in their respective service sectors (column 2 and 4).

Table A8: Effect of ADSL on occupational sorting across establishments

VARIABLES	(1)	(2)	(3)	(4)
	City level	Establishment level		
	Total	Total	Services	Manuf.
T = 0	0.00182* (0.00105)	0.000912** (0.000417)	0.00124** (0.000584)	-0.000503 (0.000716)
T = +1	0.00410*** (0.00144)	0.00173** (0.000700)	0.00232** (0.00104)	-0.00101 (0.000968)
T = +2	0.00666*** (0.00201)	0.00474*** (0.000975)	0.00559*** (0.00146)	0.000268 (0.00137)
T = +3	0.0102*** (0.00251)	0.00791*** (0.00128)	0.00853*** (0.00179)	0.00213 (0.00176)
T = +4	0.0117*** (0.00307)	0.00946*** (0.00157)	0.0104*** (0.00218)	0.00137 (0.00220)
T = +5	0.0165*** (0.00340)	0.0122*** (0.00195)	0.0129*** (0.00264)	0.00287 (0.00278)
Average effect	0.00850*** (0.00208)	0.00616*** (0.00108)	0.00682*** (0.00155)	0.000855 (0.00152)
Observations	115,962	1,683,946	1,188,815	415,923
R-squared	0.728	0.836	0.842	0.764

Notes: Column (1) runs the regression at the city level, following equation 3, where the dependent variable is the weighted average of occupational concentration within establishments (HHI) at the city level, and controls are the share of manufacturing employment, the population density in 1999 interacted with year dummies, department \times year fixed effects and city fixed effects. Standard errors are clustered at the department level. Columns (2) to (4) run the same specification on the outcome computed at the establishment level, replacing city fixed effects by establishment fixed effects. Regressions are run on the full sample, on the sample of service firms only, and on the sample of manufacturing firms only.

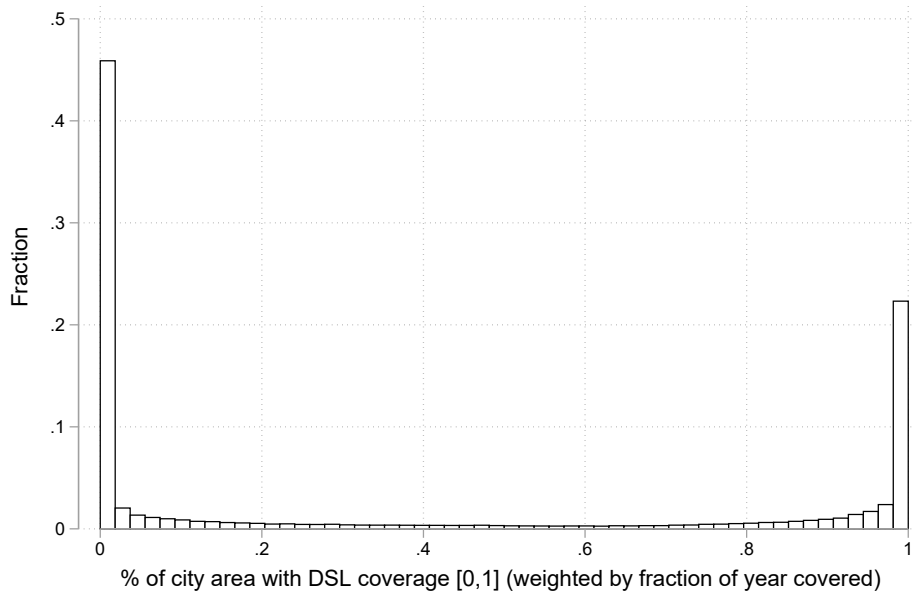
Table A9: Effect of outsourcing on sending establishments

	(1) Low-Skill outsourcing event	(2)	(3) High-Skill outsourcing event	(4)
	Log hourly wage incumbent blue collar workers	Occup. Concentration within estab (HHI)	Log wage incumbent executives	Occup. Concentration within estab (HHI)
T = 0	0.114*** (0.00532)	0.00201** (0.000880)	0.148*** (0.0110)	0.00662*** (0.00137)
T = +1	0.164*** (0.00631)	0.00203* (0.00111)	0.186*** (0.0136)	0.00938*** (0.00172)
T = +2	0.218*** (0.00784)	0.00282** (0.00138)	0.204*** (0.0177)	0.0134*** (0.00230)
T = +3	0.249*** (0.00907)	0.00381** (0.00167)	0.204*** (0.0208)	0.0182*** (0.00292)
T = +4	0.297*** (0.0111)	0.00641*** (0.00202)	0.248*** (0.0283)	0.0182*** (0.00401)
T = +5	0.338*** (0.0153)	0.00401 (0.00265)	0.274*** (0.0384)	0.0191*** (0.00559)
Average effect	0.230*** (0.00693)	0.00352*** (0.00123)	0.211*** (0.0160)	0.0142*** (0.00224)
Observations	86.325	93.432	29.143	32.78
R-squared	0.932	0.930	0.930	0.911

Notes: Controls for firm and year FE. Standard errors clustered at the firm level. Period: 2002-2007. High-skill outsourcing events at the establishment level are defined as the movement of at least one executive out of the estab. and towards a high-skill service sector (IT services or accounting). Low-skill outsourcing events are defined as the movement of at least one blue collar worker out of the estab. and towards a low-skill service sector (cleaning services, food services, security services or driving services).

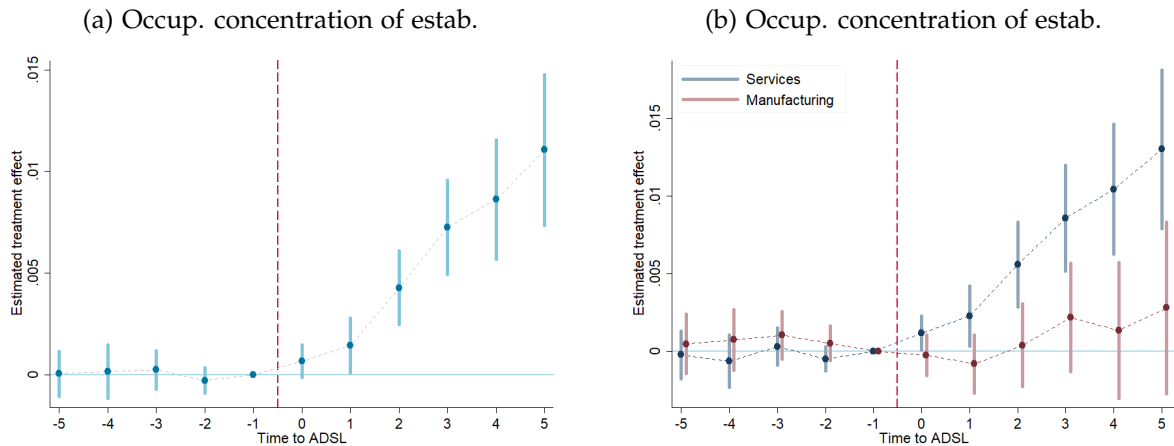
A.2 Figures

Figure A1: Distribution of \tilde{Z}_{it} : 1999-2007



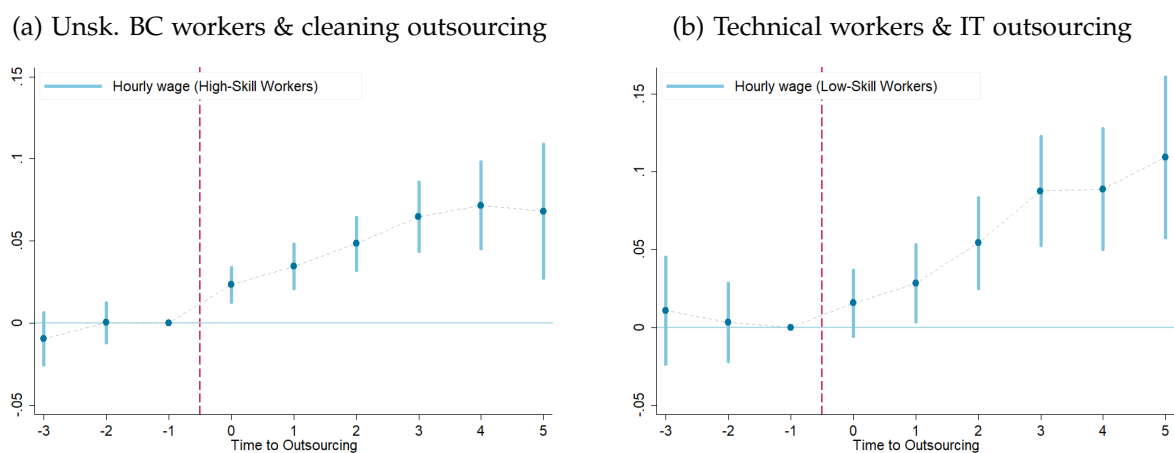
Notes: This figure plots the distribution of the continuous measure of local broadband availability (variable \tilde{Z}) as defined in Equation (1). We see that while the measure is continuous and contained between 0 and 1 but presents point of accumulation on 0 and 1.

Figure A2: Establishments' concentration of occupations and broadband access



Notes: This Figure shows regression coefficients and 95% confidence intervals from a dynamic event study where the dependent variable is the occupational concentration (measured through the HHI) within an establishment at t and the regressors are dummies for the number of years before/after broadband access. Regressions follow the specification reported in equation 3. Panel (a) and (b) report the effects for all establishments, while panel (c) and (d) distinguishes between the effect for the sample of establishments in the service sector and in the manufacturing sector.

Figure A3: Wage of incumbent workers after the outsourcing event (IT and cleaning)



Notes: This Figure shows regression coefficients and confidence intervals at ± 2 standard errors from a dynamics event study where the dependent variables are the log hourly wage of workers remaining in the establishment at time t , and the regressors are dummies for the number of years before/after the establishment experiences an outsourcing event. High-skill outsourcing events at the establishment level are defined as the movement of at least one executive out of the estab. and towards a IT service sector. Low-skill outsourcing events are defined as the movement of at least one low-skill worker out of the estab. and towards the cleaning service sector. Regression includes a set of establishment fixed effects as well as year fixed effects. Sample only include the period going from 2002 to 2007 because the event cannot be defined on earlier data. Standard errors are computed using an heteroskedastic robust variance covariance estimators allowing for autocorrelation at the establishment level.

B Data Appendix: Administrative Employer-Employee Data

Our main analysis relies on data from the administrative records that are used by the French government to compute the amount of payroll taxes. Our period of analysis spans from 1996 to 2007. The first year is chosen to include few years prior to the beginning of broadband diffusion, which started in 1999, while the last year corresponds to the final year of broadband expansion. We chose not to include later years because of the hit of the financial crisis. This data is collected yearly by *INSEE* (the French Statistics Office) and are known under the name of *DADS poste* ("*Déclarations Annuelles des Données Sociales*"). The main dataset contains information on all work contracts existing within each establishment of each firm operating in the French territory. The latter allows to follow establishments and firms over time but not workers, except for a 1-year worker panel dimension available since 2002. This is the main source that we use for the city and firm level analysis. For the worker level analysis, we rely on a subsample of this data known under the name of *DADS Panel*. The latter randomly selects 1/24th of the labor force and follows it across employment spans over the entire period. The random selection is achieved through the inclusion of all workers born in October of an odd year. The raw data provided to researchers has already undergone substantial verification, such that it requires only a minimal amount of additional cleaning.

For this study we focus on workers with some degree of attachment to the labor market ("*postes non-annexes*"), which are defined as the contracts involving either more than 120 hours of work, or more than 30 days of work with more than 1.5 hours of work per day, or that paid more than 3 times the monthly minimum wage over the year. We also exclude firms with less than 10 employees, to avoid considering family-run companies and thus focus on the formal businesses. We further exclude some occupations and industries since we are interested only in the private sector. In the following bullet points we specify the occupations that we drop and we provide their codes according to the PCS-2003 classification; and we detail the industries that we drop based on the NAF rev. 1 classification. Given that both of these classifications changed in the middle of our sample (2002), we use official crosswalk tables to identify the same groups in the earlier years.

- **Selection of occupations:** We drop the entire categories of people non-employed

($cs \in [7,9]$) and self-employed farmers ($cs = 1$). We further exclude self-employed crafts workers ($pcs = 20$), liberal professions ($pcs = 31$), university professors ($pcs = 34$), school teachers ($pcs = 42$), and clergy ($pcs = 44$).

- **Selection of industries:** We drop mining and farming ($NAF \in [1,9]$), utilities ($NAF \in [35,39]$), the entire public sector ($NAF \in [84,88]$), and social services ($NAF \geq 90$).

Once this cleaning is made, we define the main categories used in the paper as following:

- **High-skill workers:** We define high-skill workers as the combination of the category including CEOs and the category including executives, managers and engineers ($cs = 2$ and $cs = 3$).
- **Low-skill workers:** We define low-skill workers as the combination of the category including industry and services blue collar manual jobs ($cs = 6$) and the category including administrative and sales clerks ($cs = 5$).
- **Outsourceable high-skill workers:** in the analysis capturing the effect of broadband internet diffusion on the propensity of firms to outsource non-core activities, we take the IT specialists as an emblematic example of outsourceable high-skill jobs. The latter are identified as the IT engineers ($pcs = 388$) and the IT technicians ($pcs = 478$).
- **Outsourceable low-skill workers:** in the analysis capturing the effect of broadband internet diffusion on the propensity of firms to outsource non-core activities, we take the cleaners as an emblematic example of outsourceable low-skill jobs. The latter are identified with the category $pcs = 684$.
- **Outsourcing high-skill sector:** in the analysis capturing the effect of broadband internet diffusion on the propensity of firms to outsource non-core activities, we take IT services as an emblematic example of high-skill outsourcing industry ($NAF = 72$). In the analysis capturing the effect of outsourcing on salaries, we broaden the scope to include also the accounting and consulting sector, which allows us to increase the number of outsourcing events. The latter add the following categories: $NAF = 74.1$ (accounting and management consulting), $NAF = 74.4$ (advertising), $NAF = 74.5$ (HR services).

- **Outsourcing low-skill sector:** in the analysis capturing the effect of broadband internet diffusion on the propensity of firms to outsource non-core activities, we take cleaning services as an emblematic example of low-skill outsourcing industry ($NAF = 74.7$). In the analysis capturing the effect of outsourcing on salaries, we broaden the scope to include also security, food and driving services, which allows us to increase the number of outsourcing events. The latter add the following categories: $NAF = 74.6$ (security), $NAF = 55.5$ (canteens and caterers), $NAF = 60.2$ (urban and road transports).

C ADSL in France

The ADSL (Asymmetric Digital Subscriber Line) is a data communication technology that enables fast data transmission over copper telephone lines: bandwidth and bit rate are said to be asymmetric, meaning greater towards the customer premises (downstream) than the reverse (upstream). Eligibility for ADSL depends on the distance between the final customer and a *Local Exchange* (LEs), since the intensity and the quality of the analog signal decreases as it is routed over the copper lines. *Local Exchanges* are the telephone exchanges owned by the incumbent operator France Télécom into which subscribers' telephone lines end. Initially dedicated to the telephone network, LEs are essential for Internet users who subscribe to ADSL. LEs aggregate local traffic and then direct it via the so-called backbone (i.e. higher levels of the network) towards the world wide web. A key feature of the ADSL technology is that one can supply high-speed Internet by upgrading the LE while relying on the existing (copper) local loop to connect the premises of the final customers. The upgrading involves the installation of an equipment inside the LE (a DSLAM) required in order to *translate* the analogical signal – transmitted via ADSL on the local copper loop – to a numerical signal that can be transmitted to the higher levels of the network. The upgrading of local LEs is the key source of variation we will use in our empirical analysis.

ADSL roll-out in France As evidenced by [Malgouyres et al. \(2019\)](#), the deployment of the Broadband Internet technology beyond France's largest cities was slow at the beginning of the 2000's (see Table C1). Authors show that the causes for this staggered deployment are multiple. First, France Telecom (FT), the monopolistic telecom supplier, was uncertain regarding the future wholesale price he was going to be able

to charge, mainly due to regulatory reasons. Second, at the same time France Telecom had to invest massively in upgrading its LEs to ADSL, it went through an debt crisis which ended with what was essentially a government bailout in 2002. Under the impulse of the government – which increased its stake in the firm during the 2002 bailout of the firm – France Telecom pledged in 2003 to cover 90% of the French (metropolitan) population by the end of 2005, i.e. all local exchanges (LEs) with more than 1000 lines.

Table C1: Year of connection by municipality

Year of Connection	Number connected (in % of total)			
	Cities	Workers	Establishments	Population
2000	2.1	25.0	22.2	18.5
2001	6.6	35.7	34.7	28.9
2002	8.4	19.3	19.6	18.4
2003	12.4	6.7	7.8	9.5
2004	18.4	5.0	5.8	8.4
2005	23.0	4.4	5.4	8.5
2006	18.6	2.2	2.8	5.3
2007	8.8	1.6	1.7	2.5

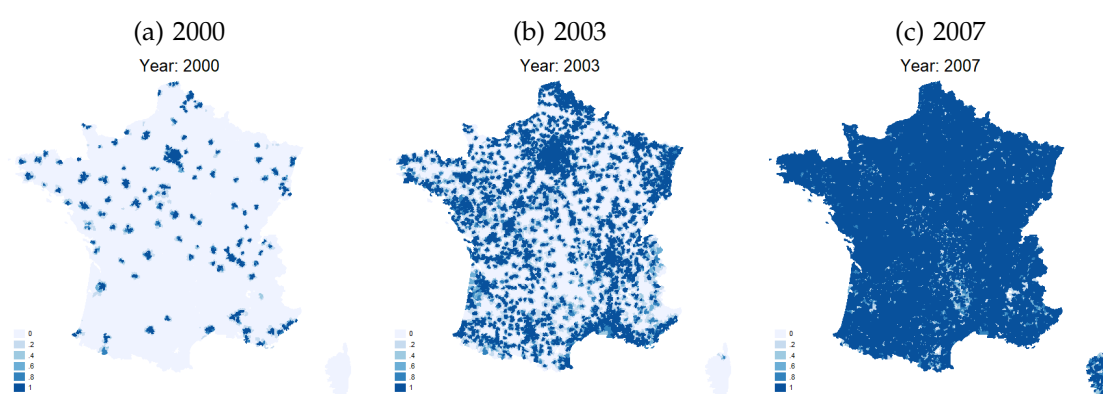
Notes: All values are taken in 1999. The sum of percentages in a column is different from 100 because a small number of cities are not connected to the ADSL in 2007. The number of establishments and workers is based on our final sample (therefore following our cleaning and selection procedures).

Between 2004 and 2007, local governments were involved in broadband internet deployment by subsidizing the expansion and favoring competition among providers. Most relevant for broadband expansion is the creation of a contract between local governments, the “Plan Département Innovant”, a contract whereby France Telecom pledged to equip all LEs with more than 100 connections within a year in that département. The proclaimed target of the plan was to raise the French population coverage up to 96% by the end of 2005 and activate all the remaining LE by the end of 2006. We account for the role of local government in our empirical analysis by including département-year fixed effects. Overall, the account of the broadband expansion in France over the period suggests that it was gradual due to uncertainty regarding the capacity of France Telecom to undergo the investment until 2002. After 2002, with the strong impulse of the government, France Telecom started covering more secondary areas with a focus on the overall number of lines per LE with only limited attention paid to local economic potential. While accelerated, the coverage remained gradual due to operational limits on the part of FT and took about 2 more years than anti-

pated in 2003.

Because our main effects of interest are identified out of the gradual diffusion of the new technology in different LEs over space and time, addressing the endogeneity of the decision to “treat” one LE before another deserves special consideration. Malgouyres et al. (2019) show that broadband expansion occurred to maximize population coverage with no special consideration for economic potential, a fact that is strongly supported by a statistical analysis of the determinants of broadband coverage that they carried out.

Figure C1: The progressive roll-out of the DSL technology in France— \tilde{Z}



Notes: This figure presents the geographical distribution of the continuous measure of local broadband availability (variable \tilde{Z}).

Use of broadband technologies by firms The ADSL technology, while progressively replaced by other technologies – notably direct access to the optic fiber or FTTO (fiber to the office) –, is the primary way for firms to access the internet. A 2016’s survey shows that 73 % of SMEs use ADSL technology as of 2016 (Arcep, 2016). The large take-up reflects the fact that ADSL was a massive improvement in terms of speed (from 56 to 512kbit/s for a transition from a classical to first generation ADSL connection) as well as in terms of cost and time of connection. While there does not exist administrative data on firm-level use of broadband, in the appendix that, based on repeated survey data, firms located in cities that received broadband internet earlier experienced a higher growth in the fraction of their employees that use internet on a regular basis between 1999 and 2004. This statistical association cannot be interpreted causally under the same set of assumptions as our main analysis. It is however strongly suggestive of an impact of broadband *availability* on broadband *adoption* and *internet use*.

Table C2: Explaining city broadband coverage: panel analysis

	(1) Covariates	(2) Twoway FE	(3) (2)+density	(4) (2)+indus.	(5) (2)+ all cov.
Lagged % primary	0.227*** (27.65)			-0.00313 (-0.13)	0.0102 (0.42)
Lagged % construction	0.0102** (2.62)			0.00890 (0.70)	0.0190 (1.62)
Lagged % auto	-0.00116 (-0.11)			0.00536 (0.19)	0.00357 (0.13)
Lagged % retail	0.0197*** (4.05)			0.00570 (0.39)	0.00646 (0.49)
Lagged % hotel	-0.00608 (-0.88)			-0.00102 (-0.05)	-0.00270 (-0.13)
Lagged % transport	0.00774 (1.42)			0.00837 (0.46)	0.0116 (0.64)
Lagged % finance	0.0340* (2.15)			0.00804 (0.23)	0.0313 (0.94)
Lagged % service_pro	0.0935*** (12.06)			-0.00520 (-0.34)	-0.00349 (-0.24)
Lagged % service_pers	0.00258 (0.58)			0.0390* (2.61)	0.0583*** (4.01)
Lagged % utilities	0.0665*** (3.36)			0.0201 (0.34)	0.0485 (0.84)
Lagged Δ % primary	-0.253*** (-17.29)			-0.0509** (-3.10)	-0.00248 (-0.15)
Lagged Δ % construction	0.00301 (0.27)			-0.00541 (-0.58)	-0.0115 (-1.33)
Lagged Δ % auto	-0.0132 (-0.51)			-0.0195 (-0.98)	-0.0208 (-1.04)
Lagged Δ % retail	0.00222 (0.17)			-0.000326 (-0.03)	-0.00234 (-0.25)
Lagged Δ % hotel	0.00606 (0.34)			-0.0119 (-0.85)	-0.0103 (-0.75)
Lagged Δ % transport	-0.0143 (-0.96)			-0.0134 (-1.12)	-0.0130 (-1.20)
Lagged Δ % finance	0.0319 (1.31)			0.0278 (1.29)	0.0198 (0.96)
Lagged Δ % service_pro	-0.0379* (-2.48)			-0.0135 (-1.01)	-0.00496 (-0.42)
Lagged Δ % service_pers	0.00973 (0.70)			-0.0190 (-1.63)	-0.0306** (-2.67)
Lagged Δ % utilities	-0.0675 (-1.34)			0.00602 (0.15)	0.0316 (0.79)
1 { year=1999 } × Ln Density 1990	-0.0402*** (-48.22)				
1 { year=2000 } × Ln Density 1990	-0.0257*** (-30.82)		0.0337*** (6.93)		0.0337*** (6.92)
1 { year=2001 } × Ln Density 1990	0.0145*** (17.41)		0.109*** (26.23)		0.109*** (26.29)
1 { year=2002 } × Ln Density 1990	0.0524*** (62.84)		0.162*** (34.28)		0.162*** (34.33)
1 { year=2003 } × Ln Density 1990	0.0881*** (105.70)		0.170*** (27.10)		0.170*** (27.05)
1 { year=2004 } × Ln Density 1990	0.129*** (155.64)		0.146*** (18.07)		0.146*** (17.96)
1 { year=2005 } × Ln Density 1990	0.170*** (205.31)		0.0904*** (12.36)		0.0903*** (12.27)
1 { year=2006 } × Ln Density 1990	0.196*** (234.58)		0.0374*** (8.11)		0.0372*** (8.10)
1 { year=2007 } × Ln Density 1990	0.206*** (247.86)		0.0162*** (5.76)		0.0162*** (5.75)
R ²	0.555	0.786	0.812	0.787	0.812
Industry: F-stat	50.73			2.57	2.18
Density: F-stat	21583.14		221.55		223.93

Notes : This table presents the R-square of panel regressions following equation (2). Twoway FE (Column 2) refers to a twoway fixed-effect model with city fixed effect and département × year FEs. Density (Column 3) includes 1999 population density at the city level defined as total population divided by city area interacted with year indicators. Industrial structure controls (Column 4) include the lagged share and their changes of sectoral shares (nine sectors). Column (1) includes all of the controls without fixed effects.

D Theoretical framework

In this section, we show how a technological shock such as broadband internet can push firm to outsource their low-skilled occupation workers, in particular for low-skilled occupations that are not considered core.

D.1 A general framework

We consider a modified version of the model presented in [Aghion et al. \(2019a\)](#). In this model, a firm is represented as a collection of N low-skilled occupations that are complementary with other assets (including high-skilled workers).

Formally, the representative firm has the following production function:

$$F(\mathbf{q}) = \theta Q \prod_{i=1}^N q_i^{\alpha_i}, \quad (8)$$

where q_i is the level of human capital in task i , Q the stock of other firm assets and θ a measure of productivity.

For each low-skilled occupation i , the firm can choose to outsource the workers. In this case, the value of q_i is fixed and equal to $\lambda_i \tilde{q}_i$ and we denote by \bar{w}_i the labor cost of this occupation. Alternatively, a firm can hire workers and train them with a quadratic cost $\mathcal{C}_i \Delta_i^2$, where $\Delta_i > 1$ denotes the increasing human capital level from λ_i . This cost can be interpreted as a training cost aiming at the development of a firm-specific human capital that complete education level. We denote $w_i(\mathbf{q})$ the labor cost associated with occupation i .

To summarize, for each occupation i :

$$(q_i, w_i) = \begin{cases} (\Delta_i \lambda_i, w_i(\mathbf{q})) & \text{if hired} \\ (\lambda_i, \bar{w}_i) & \text{if outsourced} \end{cases} \quad (9)$$

Wage formation

Following [Aghion et al. \(2019a\)](#), we model wage bargaining *a la* [Stole and Zwiebel \(1996\)](#). Workers in each occupation bargain for a wage $w_i(\mathbf{q})$ with the outside option of working in an outsourcing firm and be paid at a wage \bar{w}_i (for simplicity, we assume that the worker capture all the cost of outsourcing \bar{w}_i). Regarding the firm, hiring the

worker at a wage $w_i(\mathbf{q})$ generates:

$$F(\mathbf{q}^*) - \sum_{j=1}^N w_j(\mathbf{q}^*) - C_j \Delta_j^2$$

while outsourcing occupation i generates:

$$F(\mathbf{q}_{-i}^*, \lambda_i) - \sum_{j \neq i}^N w_j(\mathbf{q}^*) - C_j \Delta_j^2 - \bar{w}_i$$

Given the form of the production function, firm's surplus is equal to:

$$F(\mathbf{q}^*) \left(1 - \frac{1}{\Delta_i^{\alpha_i}} \right) - w_i(\mathbf{q}^*) + \bar{w}_i - C_i \Delta_i^2$$

while workers i surplus is:

$$w_i(\mathbf{q}^*) - \bar{w}_i.$$

We assume that the surplus is equally split between the firm and the worker, which yields the following equilibrium wage:

$$w_i(\mathbf{q}^*) = \bar{w}_i + \frac{1}{2} \left(F(\mathbf{q}^*) \left(1 - \frac{1}{\Delta_i^{\alpha_i}} \right) - C_i \Delta_i^2 \right). \quad (10)$$

In particular, wages change with Δ_i as:

$$\frac{dw_i(\mathbf{q}^*)}{d\Delta_i} = \frac{\alpha_i \theta Q}{2\Delta_i} F(\mathbf{q}^*) - C_i \Delta_i \quad \text{and} \quad \frac{dw_j(\mathbf{q}^*)}{d\Delta_i} = \frac{\alpha_i F(\mathbf{q}^*)}{\Delta_i} \left(1 - \frac{1}{\Delta_j^{\alpha_j}} \right),$$

Training resources

Following [Aghion et al. \(2019a\)](#), we consider that a firm only have a fixed amount of time/resources to devote to training low-skilled workers. Formally, we add a constraint to the firm's maximization problem:

$$\sum_{i \in \mathcal{H}} C_i \Delta_i^2 < T,$$

where $\mathcal{H} \subset \{1 \dots N\}$ denotes the set of occupations that are not outsourced. This constraint formalizes the idea that managers' time devoted to increasing firm-specific

human capital of low skilled occupation workers is limited. [PAPER? Garicano ? Span of control ?]

The firm's problem

A firm will then choose the set of occupations to outsource, and, conditional on not outsourcing, optimal values of Δ_i by maximizing its profit function, taking into account the limited training resources.

$$\pi(\mathbf{q}^*) = \max_{\mathcal{H} \subset \{1 \dots N\}} \left[\max_{\{\Delta_i\}_{i \in \mathcal{H}}} \theta Q \prod_{i=1}^N \lambda_i^{\alpha_i} \prod_{i \in \mathcal{H}} \Delta_i^{\alpha_i} - \sum_{i \in \mathcal{H}} (w_i(\mathbf{q}^*) - C_i \Delta_i^2) - \sum_{i \notin \mathcal{H}} \bar{w}_i \right] \quad (11)$$

$$\text{s.t. } \sum_{i \in \mathcal{H}} C_i \Delta_i^2 < T.$$

To simplify the expression, in the following, we will note

$$\Theta = \theta Q \prod_{i=1}^N \lambda_i^{\alpha_i}$$

the apparent level of productivity.

Technological shock

We model broadband expansion as a technological shock that exogenously increases the level of Θ . That being connected is associated with increasing productivity is warranted by Figure 1 which shows that treated firm experience a 2% increase in value added per employees.

D.2 A case with $N = 2$

In the case where there are two types of low-skilled workers, firms will react to an increasing productivity shock by choosing to outsource the occupation which is associated with the lowest α , that is, the occupation that is less core in the sense that it has a lower complementarity with the firm's other assets. This is because as θ increases, so does the demand in human capital q . A firm which chooses to hire and train workers will therefore be limited by its limited training resource constraint and might find it preferable to devote all this resource to the most core occupations, and outsource the others.

Without loss of generality, we will assume that $\alpha_1 < \alpha_2$. We will also consider that training cost are the same across occupation, denoted \mathcal{C} . We first consider that none of the two occupations is outsourced and take the Lagrangian of the firm maximization problem with $N = 2$.

$$\mathcal{L} = \frac{1}{2}\Theta(\Delta_1^{\alpha_1} + \Delta_2^{\alpha_2}) - \bar{w}_1 - \bar{w}_2 - \frac{1}{2}(\mathcal{C}\Delta_1^2 + \mathcal{C}\Delta_2^2) - \mu(\mathcal{C}\Delta_1^2 + \mathcal{C}\Delta_2^2 - T),$$

where we have used the expressions of wage as given in equation (10). μ is the Lagrangian multiplier which is equal to 0 if the training constraint is not saturated. Taking first order conditions with respect to Δ_1 and Δ_2 yields:

$$\Delta_1 = \left(\frac{\alpha_1 \Theta}{2\mathcal{C}(\frac{1}{2} + \mu)} \right)^{\frac{1}{2-\alpha_1}} \quad \text{and} \quad \Delta_2 = \left(\frac{\alpha_2 \Theta}{2\mathcal{C}(\frac{1}{2} + \mu)} \right)^{\frac{1}{2-\alpha_2}} \quad (12)$$

We clearly have $\Delta_1 < \Delta_2$, the firm demands a larger level of human capital for the low-skilled occupation that has the largest degree of complementarity for its other assets. In addition, both Δ_1 and Δ_2 increases with Δ .

If the constraint does not bind, then we have $\mu = 0$ and Δ_1 and Δ_2 are concave functions of Θ . There exist two cutoff values Θ_1^- and Θ_2^- with $\Theta_1^- > \Theta_2^-$ below which Δ_1 (resp. Δ_2) becomes lower than 1 and therefore occupation 1 (resp. 2) is outsourced.³² Then, as Θ increases, Δ_1 and Δ_2 are set at their optimal level of equation (12) with $\mu = 0$, until:

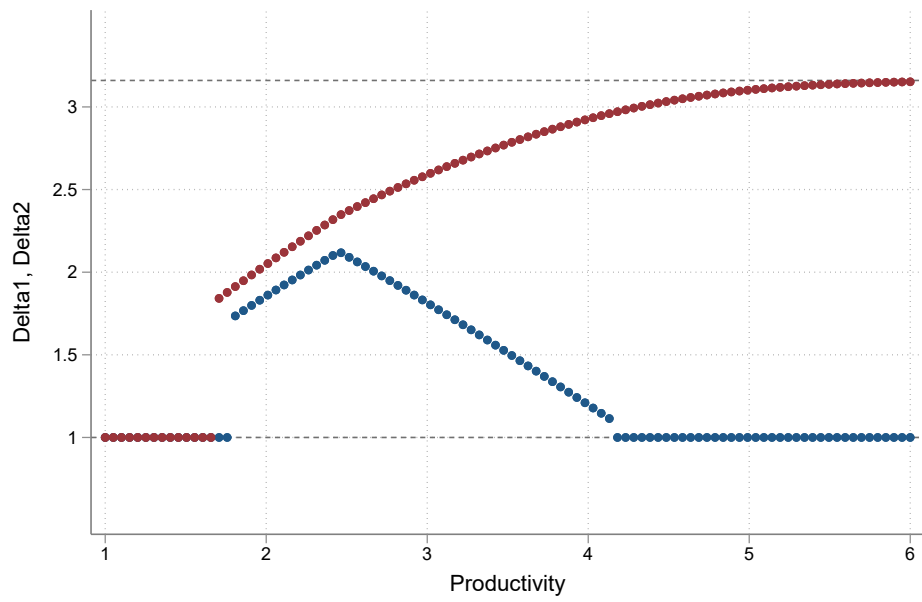
$$\Delta_1^2 + \Delta_2^2 = \frac{T}{\mathcal{C}}.$$

After this point, the training constraint is saturated and $\mu \neq 0$. Δ_1 and Δ_2 are still given by equation (12). This define a new threshold value Θ^+ . From here, in order to increase its profit, the firm will increase Δ_2 but can only do so by outsourcing occupation 1.

We simulate the model and present these results in Figure D1. Consistently with the intuition described above,

³²In fact, there exists an interval for Θ such that the firm will prefer to outsource worker even if the corresponding optimal value of Δ is larger than 1. This is because by outsourcing the worker, the firm free ride on the training cost: it cost $\mathcal{C}(1 + \varepsilon)$ to train a worker even to a very small level ε above 1.

Figure D1: Evolution of Δ_1 and Δ_2 with Θ



Notes: This figure reports the equilibrium values of Δ_1 (in blue) and Δ_2 in red for different values of Θ ranging from 1 to 6 (arbitrary values). The horizontal lines at 1 and 3.15 corresponds to the lowest and highest possible value for Δ (respectively 1 and $\sqrt{T/\bar{c}}$)

References

- Abramovsky, Laura and Rachel Griffith**, “Outsourcing and offshoring of business services: How important is ICT?,” *Journal of the European Economic Association*, 2006, 4 (2-3), 594–601.
- , —, and **Helen Miller**, “Domestic effects of offshoring high-skilled jobs: Complementarities in knowledge production,” *Review of International Economics*, 2017, 25 (1), 1–20.
- Aghion, Philippe, Antonin Bergeaud, Richard Blundell, and Rachel Griffith**, “The Innovation Premium to Soft Skills in Low Skill Occupations,” Technical Report 14102, CEPR 2019.
- , —, **Timo Boppart, Peter J Klenow, and Huiyu Li**, “A theory of falling growth and rising rents,” Technical Report 26448, National Bureau of Economic Research 2019.
- Akerman, Anders, Edwin Leuven, and Magne Mogstad**, “Information Frictions, Internet and the Relationship between Distance and Trade,” Memorandum, Oslo University, Department of Economics February 2018.
- , **Ingvil Gaarder, and Magne Mogstad**, “The skill complementarity of broadband internet,” *Quarterly Journal of Economics*, 2015, 130 (4), 1781–1824.
- Autor, David H.**, “Work of the Past, Work of the Future,” *American Economic Association Papers and Proceedings*, May 2019, 109, 1–32.
- Autor, David H, Frank Levy, and Richard J Murnane**, “The skill content of recent technological change: An empirical exploration,” *Quarterly Journal of Economics*, 2003, 118 (4), 1279–1333.
- Berlingieri, Giuseppe**, “Outsourcing and the Rise in Services,” Technical Report 1199, CEP Discussion Paper 2014.
- Biscourp, Pierre and Francis Kramarz**, “Employment, skill structure and international trade: Firm-level evidence for France,” *Journal of International Economics*, 2007, 72 (1), 22–51.
- Bloom, Nicholas, Luis Garicano, Raffaella Sadun, and John Van Reenen**, “The distinct effects of information technology and communication technology on firm organization,” *Management Science*, 2014, 60 (12), 2859–2885.

- Bonnet, Florian and Aurélie Sotura**, “Spatial disparities in France in the long run: from diverging production to converging income,” 2020. mimeo Banque de France.
- Borghans, Lex and Bas Ter Weel**, “The division of labour, worker organisation, and technological change,” *The Economic Journal*, 2006, 116 (509), F45–F72.
- Borusyak, Kirill and Xavier Jaravel**, “Revisiting event study designs,” *Available at SSRN 2826228*, 2017.
- Caliendo, Lorenzo, Ferdinando Monte, and Esteban Rossi-Hansberg**, “The anatomy of French production hierarchies,” *Journal of Political Economy*, 2015, 123 (4), 809–852.
- Caroli, Eve and John Van Reenen**, “Skill-biased organizational change? Evidence from a panel of British and French establishments,” *Quarterly Journal of Economics*, 2001, 116 (4), 1449–1492.
- Charnoz, Pauline, Claire Lelarge, and Corentin Trevien**, “Communication costs and the internal organisation of multi-plant businesses: Evidence from the impact of the french high-speed rail,” *Economic Journal*, 2018, 128 (610), 949–994.
- Davis, Donald R, Eric Mengus, and Tomasz K Michalski**, “Labor Market Polarization and The Great Divergence: Theory and Evidence,” Technical Report 26955, National Bureau of Economic Research 2020.
- DeStefano, Timothy, Richard Kneller, and Jonathan Timmis**, “Broadband infrastructure, ICT use and firm performance: Evidence for UK firms,” *Journal of Economic Behavior & Organization*, 2018, 155, 110–139.
- Drenik, Andres, Simon Jäger, Miguel Pascuel Plotkin, and Benjamin Schoefer**, “Paying outsourced labor: Direct evidence from linked temp agency-worker-client data,” Technical Report 26891, National Bureau of Economic Research 2020.
- Dube, Arindrajit and Ethan Kaplan**, “Does outsourcing reduce wages in the low-wage service occupations? Evidence from janitors and guards,” *ILR Review*, 2010, 63 (2), 287–306.
- Duranton, Gilles and Diego Puga**, “From sectoral to functional urban specialisation,” *Journal of Urban Economics*, 2005, 57 (2), 343–370.
- Eckert, Fabian, Sharat Ganapati, and Conor Walsh**, “Skilled tradable services: The transformation of US high-skill labor markets,” 2019. Available at SSRN 3439118.

- Eeckhout, Jan, Christoph Hedtrich, Roberto Pinheiro et al.**, “Automation, Spatial Sorting, and Job Polarization,” Technical Report Meeting Paper 581, Society for Economic Dynamics 2019.
- Fort, Teresa C**, “Technology and production fragmentation: Domestic versus foreign sourcing,” *Review of Economic Studies*, 2017, 84 (2), 650–687.
- Garicano, Luis**, “Hierarchies and the Organization of Knowledge in Production,” *Journal of Political Economy*, 2000, 108 (5), 874–904.
- **and Esteban Rossi-Hansberg**, “Organization and inequality in a knowledge economy,” *Quarterly Journal of Economics*, 2006, 121 (4), 1383–1435.
- Godechot, Olivier, Paula Apascaritei, István Boza, Lasse Folke Henriksen, Are Skeie Hermansen, Feng Hou, Naomi Kodama, Alena Křížková, Jiwook Jung, Marta M Elvira et al.**, “The great separation: Top earner segregation at work in high-income countries,” Technical Report, MaxPo Discussion Paper 2020.
- Goldschmidt, Deborah and Johannes F Schmieder**, “The rise of domestic outsourcing and the evolution of the German wage structure,” *Quarterly Journal of Economics*, 2017, 132 (3), 1165–1217.
- Hummels, David, Jakob R Munch, and Chong Xiang**, “Offshoring and labor markets,” *Journal of Economic Literature*, 2018, 56 (3), 981–1028.
- Lewis, Tracy R and David EM Sappington**, “Technological Change and the Boundaries of the Firm,” *American Economic Review*, 1991, pp. 887–900.
- Malgouyres, Clément, Thierry Mayer, and Clément Mazet-Sonilhac**, “Technology-induced Trade Shocks? Evidence from Broadband Expansion in France,” CEPR Discussion Papers 13847, C.E.P.R. Discussion Papers 2019.
- Michaels, Guy, Ashwini Natraj, and John Van Reenen**, “Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years,” *Review of Economics and Statistics*, 2014, 96 (1), 60–77.
- Moretti, Enrico**, *The New Geography of Jobs*, Houghton Mifflin Harcourt, 2012.
- Ono, Yukako**, “Outsourcing business services and the role of central administrative offices,” *Journal of Urban Economics*, 2003, 53 (3), 377–395.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Felipe Schwartzman, “Cognitive Hubs and Spatial Redistribution,” 2019. Mimeo Princeton.

– , – , and **Nicholas Trachter**, “Diverging Trends in National and Local Concentration,” Working Paper 25066, National Bureau of Economic Research September 2018.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter, “Firming up inequality,” *Quarterly Journal of Economics*, 2019, 134 (1), 1–50.

Stole, Lars A and Jeffrey Zwiebel, “Intra-firm bargaining under non-binding contracts,” *Review of Economic Studies*, 1996, 63 (3), 375–410.

Weil, David, *The fissured workplace*, Harvard University Press, 2014.