Diffusion of Broadband Internet and Firm Market Power in Output and Labor Markets

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Abstract

We investigate how broadband internet access affects firms market power in both product and labor markets. Combining balance sheet data for firms with matched employer-employee data, we estimate firm-level markups and markdowns. We find substantial differences across sectors and firms in the level of both markups and markdowns. For our difference-in-differences design, we exploit the staggered introduction of broadband internet in France in the early 2000s. We provide evidence that access to broadband internet increases markups. This is particularly true when firms are able to exploit the new technology to reap benefits from globalization, both through cheaper inputs and more export activity. We also show that the most productive firms primarily raise their markups in response to obtaining access to broadband internet. At the same time, markdowns fall when firms obtain access to fast internet due to more efficient worker representation. Further, we provide evidence that the internet leveled the playing field between low- and high-skilled workers. This is because low-skilled workers profit more from changing employers.
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1 Introduction

Market power for firms has been rising substantially throughout the past 30 to 40 years, in particular in advanced economies (De Loecker and Eeckhout, 2018). There are various explanations as to why market power has increased, among them weaker antitrust enforcement (Kwoka, 2017; Naidu et al., 2018), technology (Sutton, 1998; Bessen, 2020) and globalization

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(De Loecker and Warzynski, 2012; Brandt et al., 2017). It is important to understand the implications of technology on market power because rising market power implies a reallocation of resources away from consumers and workers to firm owners. This leads to a decline in welfare due to lower consumption levels through two channels: workers earn less relative to their marginal product and goods are sold at a higher price. Thus, consumers are priced out of the market (Harberger, 1954; Posner, 1975). Further, market power can stifle innovation and investment (Aghion et al., 2005), hence having adverse consequences on long-term productivity and growth.

We provide evidence on the impact of broadband internet on firm market power. Importantly, we distinguish between market power in output and labor markets by estimating firm-level markups and markdowns following Yeh et al. (2022). Markups are defined as the ratio between price and the marginal cost, and markdowns are defined as the ratio between the marginal revenue product of labor and wages. We use administrative firm balance sheet data between 1996 and 2007 in order to estimate markups and markdowns. We augment the balance sheet data with employer-employee matched in order to determine full-time equivalent employment per firm. The estimation strategy for firm market power builds on the existence of two flexible inputs, namely labor and materials. We assume a translog production function with constant parameters over the full time period and by two-digit industry.

Our identification strategy exploits that the roll-out of broadband internet in France was slow and gradual during the early 2000s. The key driver of the diffusion of the new technology was population density (Malgouyres et al., 2021). Importantly, this staggered diffusion allows us to exploit quasi-random variation in the timing of broadband connection across municipalities in the same department, controlling for population density. We take into account the vast methodological improvements in the two-way fixed-effects literature in staggered adoption contexts in our difference-in-differences setup (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Borusyak et al., 2022). We primarily use the difference-in-differences estimator by Callaway and Sant'Anna (2021) in our analyses because it has the advantage to incorporate covariates and obtain causal effects with variation in treatment timing.

Our first finding relates to the impact of broadband internet on product market power. A priori, the effect is ambiguous due to higher price transparency for consumers as well as potential cost savings for firms, which may not be passed on to consumers. We show that firm-level markups are rising after the municipality where the firm is located is connected to broadband internet. This indicates that firms reap more benefits due to increased price transparency. After five years of the introduction of broadband internet, markups increase by nearly two percentage points on average. The impact is not immediate, but starts to take its form three years after the introduction, but then rises substantially.

We investigate various mechanisms in order to understand how firms are able to increase their markups after access to faster internet connection. To test the importance of mechanisms, we estimate a triple difference-in-differences estimation strategy building on the baseline estimation strategy. First, we examine measures how firms can expand their demand, specifically through exports and by increasing their expenditure for advertising. In this exercise, we find that increasing exports plays an important role, while increasing advertising expenditure plays, if any, a minor role. Second, we look at the supply chain management of firms in the form of cheaper inputs - we use Chinese imports given that China joined the WTO at the same time as the roll-out of broadband internet occurred - and (domestic) outsourcing. We show that cheap inputs play the most important role for rising markups, implying that firms do not perfectly pass through their cost-savings due to cheaper inputs to customers. These findings indicate how important it is to consider the joint effect of technology and globalization instead of regarding them as separate phenomena.

A recent literature highlights the importance of "superstar" firms driving the increase in average markups (Autor et al., 2020; De Loecker et al., 2020). We categorize firms into four categories based on their productivity - based on value added - and their size, and estimate which firms increase their markups. Unsurprisingly, the most productive and largest firms are increasing their markups the most. Specifically, they increase their markups by two and four percentage points more than the least productive and smallest firms, respectively. Taken together with the results from the mechanisms above, this clearly shows that the most productive and largest firms are able to reap the benefits from globalization through more exports and cheaper imports, which then leads to rising markups.

The second set of findings is related to labor market power and how it changes with access to broadband internet. Both workers and firms can generate gains from the internet, where the direct effect of higher pay transparency favors workers, while the indirect effect - implying that firms adjust their wage-setting and hiring policies - favors firms. The staggered difference-in-differences design provides evidence that firm-level markdowns are falling after the municipality where the firm is located is connected to broadband internet. Markdowns fall by slightly more than three percentage points five years after the introduction of broadband internet, but the impact is occurring faster compared to markups.

We investigate various mechanisms behind the decline in markdowns, and the direction of the skill bias. We find that markdowns are falling stronger in sectors where workers are more represented through either unions or work councils. This is indicative of the internet helping unions to revitalize, e.g. through more efficient communication strategies, altering union identity and establishing different forms of internal democracy (Martínez Lucio, 2003). Diamond and Freeman (2002) highlight that unions have to be proactive in this process, and that the benefits of the internet do not occur automatically. The skill bias of broadband internet is a priori not clear. We identify the direction of skill bias by leveraging worker-level wage data as well as differentiating labor types in the firm balance sheet data. We find that low-skill workers experience stronger wage growth after getting access to broadband internet compared to high-skill workers. This is primarily driven by workers changing their employer. At the firm-level, we find that low-skill workers are subject to greater markdowns, but the firms in the sample based on balance sheet information are not representative as they tend to be larger firms.

We contribute to various strands of the literature. First, we contribute the literature on the determinants of market power on output markets. They can be categorized in two types of studies, namely the micro level, which discuss single industries in substantial detail, and the macro level, which are typically more descriptive in nature. At the micro level, technological advancement primarily relate to the production process or the logistical setup (Miller et al., 2022; Grieco et al., 2022; Ganapati, 2021). These studies do not paint a clear picture across the different industries, ranging from cement, automobile and wholesale. At the macro level, a large focus is put on (proprietary) IT investments and largely indicate that technological advances lead to rising markups and/or concentration, but often remain descriptive in nature (De Loecker and Eeckhout, 2018; Calligaris et al., 2018; Bessen, 2020). Alternatively, there is theoretical work on the relationship between technological progress and market power, e.g. Aghion et al. (2019). We contribute to this literature by studying a different type of technological advance, namely the diffusion of broadband internet, and by concentrating on market power in both output and labor markets. The diffusion of broadband internet constitutes two key differences to the technologies previous work focuses on in order to understand the impact on market power: First, the diffusion of broadband internet is paid for by the state instead of the firms. This means that firms “only” have to invest in the necessary IT infrastructure and software in order to exploit the benefits from this technology. Secondly, we overcome the inherent difficulty to obtain plausible exogenous variation, in particular as the use of internet and information and communication technology are management decisions in most cases. In short, this study sheds light on a different type of technology with rather low fixed costs due to government investment, exogenous variation and the focus on both markups and markdowns.

Second, we relate to recent work on the impact of the diffusion of broadband internet, e.g. Malgouyres et al. (2021) show that access to broadband internet raises firm imports in France, and Bergeaud et al. (2022) provide evidence that spending on domestic outsourcing increases with exposure to the new technology in France. Further, Mazet-Sonilhac (2022) documents that the faster internet connections affects the allocation of credit and firm-bank matching due to reduction in search frictions, and reduced the cost of debt for small businesses. Akerman et al. (2015) show that broadband internet improves firm productivity and is skill-biased in Norway. We contribute to this literature by investigating the impact on firm market power. Importantly, we differentiate by market power in output and labor markets by measuring both markups and markdowns. Further, we investigate the mechanisms behind our findings.

The paper is organized as follows. In the subsequent section we discuss the theoretical mechanisms how the adoption of broadband internet affects firm market power in both output and labor markets. Section 3 provides details on the estimation of markups, markdowns and the impact of technology on each type of market power. In Section 4 we present the French data sources, ranging from the administrative data to the roll-out of broadband internet, as well as descriptive statistics. Section 5 presents the key empirical findings how the diffusion of broadband internet affects market power on product and labor markets, and 6 provides various sensitivity analyses. Section 7 concludes.

2 How can Broadband Internet affect Market Power?

Broadband internet constitutes an upgrade to existing technology. The upgrade encompasses the supply of high-speed internet (nine-fold increase) at lower cost and faster time of connection with the internet. Overall, the impact of broadband internet on both markups and markdowns is ambiguous because all agents in the economy experience a reduction in information frictions as well as lower search costs. Examples include consumers comparing prices online given that firms are increasing their online presence, workers and firms can now match online in the labor market, communication is greatly facilitated by e-mail services, and file sharing and digital storage of information are increasingly important.

The internet affects both firms and (potential) customers on the product market: the shift to e-commerce and e-services has various advantages to firms ranging from centralized inventory, reduced facilities costs and self-sourcing (Boyer, 2001). Further, many services can be offered more economically with greater geographical reach (Boyer et al., 2002). It also allows firms to improve their marketing and advertising in order to increase demand for their products. Further, they can improve their supply chain management, e.g. in the form of new and more imported goods (Malgouyres et al., 2021) or in the form of (domestic) outsourcing (Bergeaud et al., 2022). Finally, the production process can also improve and become more efficient due to more efficient organization in the firm (Bartelsman et al., 2019; Grimes et al., 2012). All these factors contribute to cost-savings and to a reduction of marginal cost of production. Hence, markups will increase if the cost-savings are not passed on completely to consumers.

On the other hand, consumers can compare prices easier and faster on the internet. The increase in price transparency on the consumer side (lower search costs or higher share of fully informed consumers) should lead to a decline in prices through heightened competition. As a consequence, markups fall all things equal. In other words, the demand elasticity of firms increases (in a static setting) implying that the market becomes more competitive. However, in a dynamic setting, firms have an incentive to collude and to earn higher markups. But Schultz (2005) argues that in markets with sufficiently differentiated goods, the incentive to undercut the collusive price is larger than the punishment from deviating from the collusive price. Given that the internet increases product variety (Brynjolfsson et al., 2003), markups should fall due to price transparency on the consumer side in both static and dynamic settings.

Turning to monopsony power, the internet has a profound impact on both firms and workers on the labor market.[1] On the worker side, broadband internet raises information about out-

[1] See e.g. Autor (2001) for a contemporaneous outlook on how the internet may affect various labor market features.

side options for workers, both relating to employment itself as well as the wage. Ensher et al. (2002) mention that workers become increasingly aware of how their contemporaneous employers compares to other employers in terms of both salaries and other compensation schemes.[2] Further, the internet allows workers to train and develop based on their interests and demand for certain skills. If these skills are transferable across organizations, this will also provide them with more bargaining power, and consequently reduce markdowns. Finally, the internet facilitates better communication and coordination among employees and their representatives in wage bargaining institutions. These channels should allow workers to increase their bargaining power and therefore be subject to lower markdowns.

On the other side, internet access can increase labor productivity and surveillance of workers. Nurmilaakso (2009) provides firm-level evidence on a cross-section of European firms that internet access significantly increases labor productivity, and Najarzadeh et al. (2014) show that labor productivity rises with access to the internet based on dynamic panel data for 108 countries. If the labor productivity climb is not compensated fully to wages, then markdowns will increase. The internet also allows for worker surveillance, e.g. Ball (2010) argues that "[...] Internet is largely responsible for an increase in employee monitoring" in previous years, where monitoring can take the form of personal data gathering, internet and email monitoring and location tracking. The efficiency wage literature suggests that employers can decrease the wage surplus they have to pay employees in order to exert (unobservable) effort. Further, worker surveillance can be used by employers to limit worker bargaining power and therefore lead to lower wages for workers. Ultimately, both channels imply that internet access increases markdowns.[3]

A large literature has also focused on the skill-bias of technological progress. The case of broadband internet is no exception of the possibility of some bias (Bergeaud et al., 2022; Akerman et al., 2015). On the one hand, Ensher et al. (2002) mention that especially highly technical employees ask for compensation plans above market levels. Further, Skott and Guy (2007) highlight that these technologies also allow firms to monitor their workers substantially better, which hits low-skilled workers substantially harder than high-skilled workers. On the other hand, broadband internet may also help low-skill workers more as they are more likely to anchor their wages on current earnings (Jäger et al., 2021). Hence, reducing information frictions can reduce monopsony power for firms for both low- and high-skill workers. Thus, the diffusion of broadband internet can contain a skill-bias, but ultimately it depends on who exploits the reduction in information frictions better. However, even if there is a skill bias, both types of

[2]Examples include stock options and pension plans as they focus on the United States.

[3]Cullen and Pakzad-Hurson (2023) highlight a third channel, namely the indirect effect of pay transparency, namely the adjustment with respect to wage bargaining. They provide theoretical and empirical evidence (for the United States) that higher transparency reduces average wages because the firm's willingness to pay higher wages increases with individual workers in order to avoid costly renegotiations with other workers. Jäger et al. (2021) corroborate this finding by providing evidence from a personnel manager survey in Germany, where 31% say that one reason for not increasing salaries is that negotiating with individual employees would trigger additional wage negotiations with other employees.

workers can be better off relative to their marginal revenue product of labor overall.

In summary, the theoretical impact of the expansion of broadband internet is ambiguous on both firm market power in product and in labor markets. While in theory everyone gains from the reduction in information frictions in the economy due to better and faster connectivity, the question remains who gains most. Therefore, it is ultimately an empirical question how broadband internet how markups and markdowns change after the introduction of the introduction of broadband internet.

3 Estimation Procedures

3.1 Measuring Markups and Markdowns

We estimate firms' market power in the output market and in the labor market with markups and markdowns, respectively. We define markups as the price over marginal cost, and markdowns as the marginal revenue product of labor over wages paid. In output markets firms have market power due to downward-sloping product demand curves, while market power in the labor market comes from upward-sloping labor supply curves.[4]

3.1.1 Theoretical Foundation

We measure both markups and markdowns based on the "proxy variable approach" by Levinsohn and Petrin (2003), De Loecker and Warzynski (2012) and Ackerberg et al. (2015). The key advantage of this approach is its flexibility with respect to the underlying production technology, consumer demand and market structure. Specifically, we follow Morlacco (2019) and Yeh et al. (2022) whose methodology allows us to differentiate between market power in output and labor markets. It relies on optimal input demand conditions obtained from firm cost-minimization and the ability to identify the output elasticity of two flexible inputs. The key assumption encompasses that the firm possesses buyer power for one flexible input, whereas the market for the other flexible input is characterized by perfect competition.[5] Based on the two output elasticities, the authors show how to estimate markups and markdowns separately based on both the output elasticities and expenditure shares for two flexible inputs.

Here, we want to focus on the main formulas for total firm market power, which is defined as the market power firms exert in both output and labor markets, as well as markups and markdowns. We provide more detail on the theoretical derivation in Appendix A. In short, we set up the Lagrangian for a cost-minimizing firm and optimize it with respect to two flexible inputs, namely materials and labor. We then make use of different simplifications in order to obtain the

[4] While downward-sloping product demand curves are plausible, upward-sloping labor supply curves need not be the only source of market power, especially in the viewpoint of the search-and-matching literature, e.g. Mortensen and Pissarides (1994).

[5] The standard setup of the proxy variable approach, e.g. De Loecker and Warzynski (2012), assumes that there is just one flexible input with the assumption of perfect competition in the market for this input, typically labor.

formulas for total market power, markups and markdowns.
The ratio of output elasticity of labor relative to the expenditure share encompasses both labor market power and product market power. Specifically, we have:

$$\Xi_{jt} \ = \ \mu_{jt} \cdot \upsilon_{jt} \ = \ \frac{\theta^L_{jt}}{\alpha^L_{jt}}, \tag{1}$$

where Ξ_{jt} represents the *total* market power of a firm. It is equal to the ratio of the output elasticity with respect to labor (θ^L_{jt}) over the labor expenditure share (α^L_{jt}). A key understanding from the "production approach" is that wedges between output elasticities and expenditure shares can reflect market power. Intuitively, the output elasticity of labor captures the benefit from an additional unit of labor, whereas expenditure share of labor reflects its cost. However, as Syverson (2019) points out, this ratio reflects both market power in output markets in the form of markup μ_{jt} and market power in labor markets in the form of the wage markdown υ_{jt}.[6]
We can derive markups from equation (15b) using three simplifications, namely the left-hand side being equivalent to the output elasticity with respect to materials (θ^M_{jt}), the definition of markups, and the definition of the expenditure share with respect to materials. These simplifications imply:

$$\mu_{jt} = \frac{\theta^M_{jt}}{\alpha^M_{jt}}, \tag{2}$$

where markup μ_{jt} can be expressed by the ratio of the output elasticity with respect to materials over the expenditure share of materials. This can be generalized to any flexible input, where the input market is characterized by perfect competition. When firms possess monopsony power, then labor is an unsuitable flexible input to estimate markups.
We can pin down markdowns using equations (1) and (2). Through substitution, it is straightforward to show that:

$$\upsilon_{jt} = \left(\frac{\theta^L_{jt}}{\alpha^L_{jt}}\right)\left(\frac{\theta^M_{jt}}{\alpha^M_{jt}}\right)^{-1}, \tag{3}$$

where the markdown is defined as the ratio of the output elasticity with respect to labor over the expenditure share of labor multiplied by the inverse of the markup from equation (2).
It is important to note that υ_{jt} represents the markdown on wages relative to the markdown on materials, i.e. $\frac{\upsilon^L_{jt}}{\upsilon^M_{jt}}$. This is because we assume perfect competition in the market for material inputs. Following a similar logic, Morlacco (2019) provides evidence on dispersion in market power on material in international markets under the assumption that the domestic market is perfectly competitive.

[6] In the "standard" setup with one flexible input, e.g. De Loecker and Warzynski (2012), this ratio typically reflects markups only instead of total market power.

3.1.2 Estimation

The empirical implementation of the markup and markdown estimation requires two further assumptions common in the "proxy variable" literature. They are necessary to estimate the output elasticity of both labor (θ^L_{jt}) and material (θ^M_{jt}). First, we assume that each firm has a translog production function for gross output in capital, labor and materials, and that the production function parameters are constant over time and common within an industry (measured at the two-digit level of NACE Rev. 2). Second, we assume that a firm's productivity is Hicks-neutral, implying that changes in productivity do not affect the relationship between input factors. Further, material inputs are monotonic in productivity, which is in line with a large class of models of imperfect competition.

In order to recover the output elasticities of labor and materials, we assume a translog production function for gross output. The translog production function allows for variation in output elasticities in time, opposite to a Cobb-Douglas production function. With Cobb-Douglas production function, variation in markups and markdowns over time comes entirely from expenditure shares. We will primarily rely on results based on the translog gross output production function, but will also report results based on a Cobb-Douglas production function.

Our estimation strategy to estimate the production function parameters (β) encompasses two steps. For the first step, consider a gross output translog production function:

$$\begin{aligned} y_{jt} =& \beta_l l_{jt} + \beta_k k_{jt} + \beta_m m_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{mm} m_{jt}^2 + \\ &+ \beta_{lk} l_{jt} k_{jt} + \beta_{lm} l_{jt} m_{jt} + \beta_{km} k_{jt} m_{jt} + \omega_{jt} + \varepsilon_{jt}, \end{aligned} \tag{4}$$

where we denote logged output as y_{jt}, and (logged) inputs are expressed by labor (l_{jt}), capital (k_{jt}) and materials (m_{jt}), and ω_{jt} denotes the Hicks-neutral productivity parameter. As is common in the "proxy variable" literature, we rely on the monotonicity of materials in productivity, which allows us to proxy the technological parameter with $\omega_{jt} = h_t(m_{jt}, k_{jt}, \mathbf{a_{jt}})$. The vector $\mathbf{a}_{jt}$ captures additional variables potentially affecting optimal input.[7] This approximation of firm productivity then implies that the first stage estimation takes on the following form:

$$y_{jt} = \phi_{jt}(l_{jt}, k_{jt}, m_{jt}, \mathbf{a}_{jt}) + \varepsilon_{jt}, \tag{5}$$

from which we obtain estimates of predicted output $\hat{\phi}_{jt}$ and an estimate for the residual $\hat{\varepsilon}_{jt}$. Equipped with the estimate for predicted output, we can construct the productivity parameter:

$$\begin{aligned} \omega_{jt} =& \hat{\phi}_{jt} - \beta_l l_{jt} - \beta_k k_{jt} - \beta_m m_{jt} - \beta_{ll} l_{jt}^2 - \beta_{kk} k_{jt}^2 - \beta_{mm} m_{jt}^2 + \\ &- \beta_{lk} l_{jt} k_{jt} - \beta_{lm} l_{jt} m_{jt} - \beta_{km} k_{jt} m_{jt}, \end{aligned} \tag{6}$$

[7] We use year- and region-fixed effects. We use "département" as the regional level for the estimation of market power, of which 96 exist in mainland France.

which we exploit for the second stage. Specifically, we rely on the law of motion for productivity, which provides estimates for all coefficients of the production function. In line with the previous literature, we regress ω_{jt} on the third polynomial of its lag:

$$\begin{aligned}\omega_{jt} =& g(\omega_{jt-1}) + \xi_{jt}, \\ \omega_{jt} =& \gamma_1\omega_{jt-1} + \gamma_2\omega^2_{jt-1} + \gamma_3\omega^3_{jt-1} + \xi_{jt},\end{aligned} \tag{7}$$

where ζ_{jt} denotes productivity shocks to the firm. The final part of the second step is to form moments to obtain our estimates of the production function using standard GMM estimation techniques, where we rely on a vector of instrumental variables z_{jt}, which consists of one-period lagged values of every polynomial term containing labor (l_{jt}) and materials (m_{jt}), while capital (k_{jt}) is measured at its current value. These moments are suggested by Ackerberg et al. (2015) and applied throughout the "proxy variable" literature. The underlying idea is that capital is assumed to be decided a period ahead and therefore related with the innovation. Further, the necessary assumption for the validity of the instruments is that input prices for labor and materials are correlated over time.

Given the production function parameters, we can calculate output elasticities based on the derivatives of the translog gross output production function with respect to labor and materials:

$$\hat{\theta}^L_{jt} = \hat{\beta}_l + 2\hat{\beta}_{ll}l_{jt} + \hat{\beta}_{lk}k_{jt} + \hat{\beta}_{lm}m_{jt}, \tag{8a}$$

$$\hat{\theta}^M_{jt} = \hat{\beta}_m + 2\hat{\beta}_{mm}m_{jt} + \hat{\beta}_{km}k_{jt} + \hat{\beta}_{lm}l_{jt}. \tag{8b}$$

Under a Cobb-Douglas production function, the output elasticities are equal to $\hat{\beta}_l$ and $\hat{\beta}_m$, respectively.

In the last step we measure the expenditure shares for both labor and materials in order to compute both markups and markdowns based on equations (2) and (3). However, we do not observe the correct expenditure shares because we only observe $\tilde{Q}_{jt} = Q_{jt}exp(\varepsilon_{jt})$. The first stage in equation (5) provides us with an estimate for ε_{jt}. This correction eliminates any variation in expenditure shares from variables impacting input demand such as input prices, productivity, technology parameters, and other market properties, such as the elasticity of demand and income levels. Specifically, we measure the corrected expenditure shares for labor and materials as:

$$\alpha^L_{jt} = \frac{P^L_{jt} \cdot L_{jt}}{P_{jt}\frac{\tilde{Q}_{jt}}{exp(\hat{\varepsilon}_{jt})}} \tag{9a}$$

$$\alpha^M_{jt} = \frac{P^M_{jt} \cdot M_{jt}}{P_{jt}\frac{\tilde{Q}_{jt}}{exp(\hat{\varepsilon}_{jt})}}, \tag{9b}$$

Equipped with the output elasticities for materials and labor, as well as the corrected expenditure shares, we can calculate firm-level markups and markdowns based on equations (2) and (3).

3.2 Estimating the Impact of Technology on Market Power

After estimating firm-level markups and markdowns, i.e. our variables of interest, we to to identify the causal effect of broadband expansion on market power. We exploit the staggered introduction of broadband internet across municipalities during the early 2000s. Specifically, we estimate the model:

$$Y_{jct} = \sum_{\tau=-k}^{k'} \beta_\tau \mathbb{1}\{t = t_c + \tau\} + \theta_t X_{ct} + \gamma_j + \varepsilon_{jct}, \tag{10}$$

where Y_{jct} indicates the outcomes of interest, i.e. markups or markdowns, of firm j in municipality c in year t. t denotes the year of arrival of broadband internet, and X is a vector of control variables. Most importantly, it contains the population density in 1999 (based on the French Census) interacted with year-fixed effects. Finally, we add firm-level fixed effects (γ_j), implying that the comparison group are firm in municipalities with similar density within the same department that have yet to be connected with the new technology.[8] Depending on the outcome variable we use different weights, but for markups and markdowns we restore the sectoral composition such that it is representative of the French economy, given that sectoral shares change substantially in our data cleaning process. To be precise, for markups we weigh observations by the product between output and the weight to recreate the sectoral composition, and for markdowns we weigh observations by the product between employment and the weight to recreate the sectoral composition.

In our benchmark analyses, we apply the difference-in-differences (DiD) estimator proposed by Callaway and Sant'Anna (2021) because it seems the most suitable to our setting. First, like many other estimators, it is applicable for multiple time periods. Second, it allows for variation in treatment timing similar to other work by Borusyak et al. (2022), De Chaisemartin and d'Haultfoeuille (2020) and Goodman-Bacon (2021). Third and most importantly, the estimator requires that the parallel trends assumption holds only after conditioning on covariates. In our case, this is particularly important as the roll-out of broadband internet was primarily driven by population density, for which we control in all our specifications.[9] The feature of flexibly incorporating covariates into the staggered DiD setup with multiple groups and multiple periods. This is particularly important in applications in which differences in observed characteristics create non-parallel outcome dynamics between different groups.

An alternative specification is to use stacked difference-in-differences approach compared to

[8] When aggregating data to the municipality level, we include municipality-fixed effects instead of firm-fixed effects.

[9] See Section 4.2 below for more information on the precise roll-out of broadband internet.

the estimator by Callaway and Sant'Anna (2021). It has been applied by Bergeaud et al. (2022), Vannutelli (2022), Cengiz et al. (2019) and Deshpande and Li (2019). However, Baker et al. (2022) show that these two approaches yield similar results. Therefore, we concentrate on the estimator by Callaway and Sant'Anna (2021).

4 Data

4.1 French Administrative Data

In order to understand the impact broadband internet diffusion on firms' market power on product and labor markets, we primarily use balance sheet data for France. Balance sheet information is crucial to estimate markups and markdowns on the firm level. Specifically, we use *Fichier Complet Unifié de SUSE* (FICUS), which covers the years 1994 until 2007.[10] FICUS contains information on the wage bill, the capital stock, material inputs and gross output, as well as value added, though we do not use this measure in our estimation of markups and markdowns.

However, FICUS does not readily provide the full-time equivalent employment per firm, the remaining crucial variable to estimate markups and markdowns on the firm-level.[11] In order to measure full-time equivalent employment consistently on the firm level, we merge FICUS with French employer-employee matched data, specifically the *Déclaration Annuelle de Données Sociales* (DADS), which is available from 1996 onwards. DADS Salariés contains information on workplace location, wages, hours worked, occupation, industry, seniority, gender and age. The data is collected by the French National Institute for Statistical and Economic Studies (INSEE), and it covers all French private and public sector workers. Abowd et al. (1999) describe this data set in more detail.

Among the successfully merged firms, we obtain the total number of employees working in a given firm by the number of observations in the DADS. We exploit the number of hours worked in a given year in order to determine the full-time equivalent employment. Specifically, we set 2,028 hours (52 weeks times 39 hours per week) per year as the benchmark for the years prior to 2002, and post 2002 our benchmark is equal to 1,820 hours (52 weeks times 35 hours per week).[12] We have information in FARE (successor balance sheet data to FICUS) on full-time equivalent employment per firm, we can compare our measure based on the DADS from 2008 onwards. The correlation coefficient based on 6.69 million firm-level observations is equal to 0.89, and the average full-time employment per year for this period is equal to 14.32 based on the DADS data, and 14.51 based on the ESANE data set.

[10] SUSE stands for *Systéme Unifié de Statistique d'Entreprises*.

[11] Instead, FICUS provides the average salary per employee and the total amount of salaries. However, the former is subject to substantial selection bias as it is only reported for larger firms, but missing for small and medium-sized firms (based on output).

[12] This timing is in line with the reform in France to reduce the weekly working time from 39 to 35 hours. Further, the number of hours chosen also corresponds to the annual mode of hours worked.

Ultimately, we deflate all values in our estimation for markups and markdowns using deflators from Eurostat. However, they are available only for NACE Rev. 2, which was implemented in 2008, after the end of the time period subject to investigation. To allow for a precise merge, we define all sectors (2-digit) and industries (3-digit) based on NACE Rev. 2 for the estimation of markups and markdowns. For the conversion from NACE Rev. 1.1 to Rev. 2, we apply the conversion table from INSEE.

In Appendix C, we explain in detail our sample selection criteria, which are primarily based on previous literature. We also elaborate how this procedure changes our sample in terms of firm characteristics and sectoral composition.

4.2 Broadband Internet Access

We exploit data on the expansion of broadband internet in France between 1997 and 2007 by Malgouyres et al. (2021).[13] The authors manually collect the date of the upgrade to ADSL (Asymmetric Digital Subscriber Line) in mainland France for each Local Exchange (LE). This technology/update allows fast transmission over copper telephone lines.

Importantly for our research design, the roll-out of ADSL in France was gradual for multiple reasons. They relate to the monopolist supplier France Télécom: first, there was uncertainty associated with respect to the wholesale price it was going to charge its customers. Second, in the course of upgrading the technology, the company went through a tremendous debt crisis, which ended in a government bailout in 2002. With the bailout, the government increased its stake in the firm, urged France Télécom to cover 90% of the French (mainland) by the end of 2005. Between 2004 and 2007, local governments subsidized the expansion of the ADSL technology. In order to leverage the staggered roll-out of broadband internet, Malgouyres et al. (2021) show that broadband expansion occurred to maximize population coverage with no special consideration for economic potential, a fact that is strongly supported by the statistical analysis of the determinants of broadband coverage.

Firms also strongly use broadband after it is accessible to them. ADSL is the main way how firms access the internet. A survey from 2016 shows that 73% of firms of SMEs use the ADSL technology (Arcep, 2016). This reflects the massive improvements associated with ADSL: speed rose from 56 to 512 kbit/s from the previous to the contemporaneous technology. There is no firm-level administrative data on the use of the ADSL technology, but repeated surveys indicate that employees in firms located in cities that gained access to the update earlier are more likely to use internet on a regular basis between 1999 and 2004. Of course, this cannot be interpreted causally, but it is strongly suggestive of an impact of broadband availability on broadband adoption.

Following Bergeaud et al. (2022), we measure broadband access as a continuous measure for location l in year t denoted by $\tilde{Z}_{lt}$. It is a time-weighted percentage of area covered in munici-

[13] We are very grateful to Clément Mazet-Sonilhac for sharing the data with us.

pality c. It is formally defined as:

$$\tilde{Z}_{lt} = \sum_{b \in l} D_{b,t} \frac{A_{b,t}}{\sum_{b \in l} A_{b,t}}, \tag{11}$$

where b indicates the census blocks included in location l, and $D_{b,t}$ is the share of days of year t in census block b with broadband internet (BI) access. Lastly, A denotes the area by census block b. The variable is continuous within the range from 0 to 1. However, Bergeaud et al. (2022) show that there is strong concentration on the extreme values, with few intermediate values. This allows us to discretize the event of BI ($\tilde{Z}$) without a large loss of information. Specifically, we define the year of treatment as the year when $\tilde{Z}$ experiences the largest increase as in Malgouyres et al. (2021). We denote the corresponding binary variable with $C_{l,t}$.

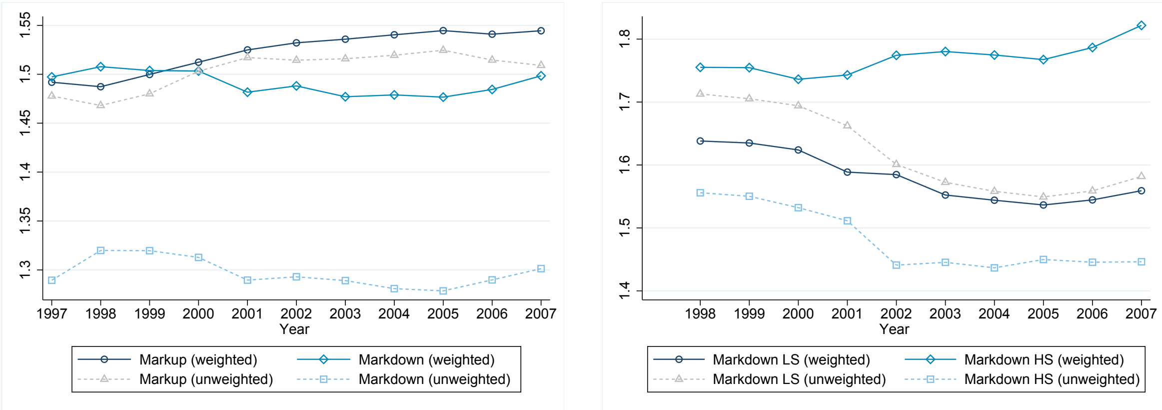
In Figure C4 in the appendix, we show the broadband expansion in mainland France between 2000 and 2006 in two-year steps. In 2000, only a small set of communities is connected to broadband internet, largely focused around larger cities, such as Paris and Lyon. In total, 744 out of 36,026 municipalities are connected to broadband internet. In 2002, we observe an increase in connected communities, i.e. 6,223 communities have access to broadband internet. In 2004, nearly half of all communities, 17,401 in total, are connected to broadband internet. In particular large cities and coastal regions have been connected until 2004, whereas rural areas are not yet connected. This changes until 2006, when 32,853 communities, i.e. 91.19 percent, have now access to a faster internet connection. Not shown in our maps, but in 2007 all communities now have access to fast internet.

4.3 Descriptive Statistics

In this section, we provide some evidence of how market power changes over time, differs across sectors and how it is regionally distributed across mainland France. The figures in this section are based on the final sample which we use for our difference-in-differences estimation below. In the appendix, we provide the same figures based on the post-market power estimation sample. Overall, there are no strong differences in time trends, sectoral averages and geographical variation across the two samples. Finally, we also present summary statistics on the firm and the municipality level for the sample we use in our analysis.

The left panel of Figure 1 shows how markups and markdowns evolve between 1997 and 2007 in France. It shows both weighted and unweighted averages, where we weigh markups by output and markdowns by employment. Markups (weighted and unweighted) are increasing between 1997 and 2007, and weighted markups are slightly larger than unweighted markups, indicating a heavier right tail across the firm output distribution. Weighted markups increase from 1.58 to 1.66. Further, the gap between weighted and unweighted markdowns is increasing slightly. Markdowns, on the other hand, are decreasing between 1997 and 2007, albeit the main decline occurs pre-2002 Post-2005, there is a small increase in markdowns. Weighted markdowns fall from around 1.65 to 1.63, but reach a low of 1.61 in 2005. There is a substantial gap between the unweighted and weighted markdown series, indicating that large firms are exerting higher labor market power than small firms, in line with standard monopsony theory.

Figure 1: Market Power Trends



(a) Markups and Markdowns

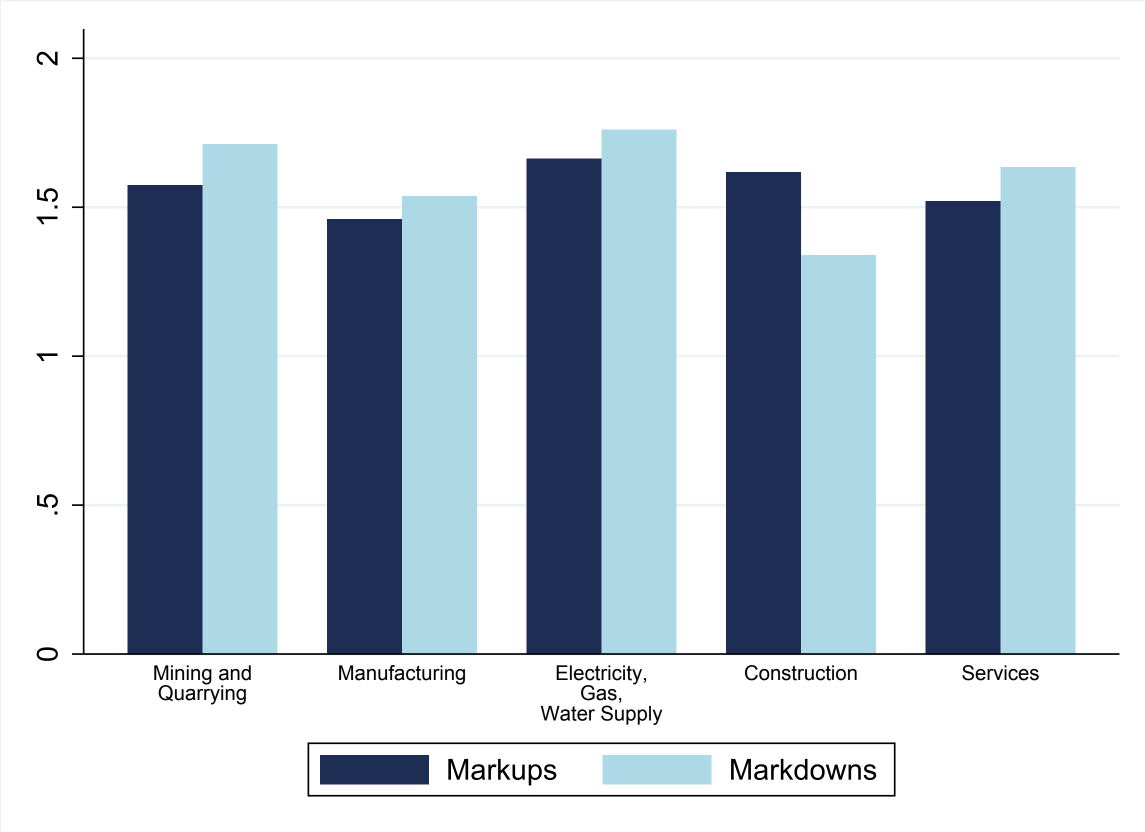
(b) Markdowns by Skill

Notes: This figure shows the evolution of market power in both product markets and labor markets, both unweighted and weighted. Markups are weighted by sales, and markdowns are weighted by employment. The right panel differentiates markdowns by skill, and contains only markdowns for firms which employ both low- and high-skilled workers. These markdowns are weighted by the share of low- and high-skill employment, respectively.

The right panel of Figure 1 presents markdowns divided by skill group. We define company managers, executives and higher professional professions as high-skilled workers, and the remaining occupations as low-skill workers. Importantly, this includes only firms where both high- and low-skill workers are employed at the same time, which reduces the number of observations substantially. Specifically, we only observe both types of labor in around 25% of the firms included in the final sample. This sample is also subject to strong selection bias because large firms are more likely to employ both low- and high-skilled workers at the same time. We weigh markdowns by the number of full-time equivalent employment of the respective skill, i.e. markdowns for low-skilled workers by low-skill employment, and markdowns for high-skilled workers by high-skill employment. The unweighted series weighted markdowns for low-skill employment are declining over time, whereas the weighted markdown for high-skill employment is not changing much. Further, the markdown for high-skill employment is considerably larger than the one for low-skilled workers, in particular for the weighted series (2.3 compared to 1.65). One reason for the lower markdowns for low-skilled workers in France could be due to a strong minimum wage, which is more binding for low-skilled workers.

Many studies of markups focus on manufacturing firms due to better data availability over longer time periods (De Loecker and Warzynski, 2012; Yeh et al., 2022). Other studies trying to extend the coverage beyond the manufacturing sector work with publicly traded firms, which typically implies a substantial reduction in sample size (De Loecker et al., 2020; Weche and

Figure 2: Market Power by Industry



Notes: This bar chart shows the average markups and markdowns weighted by sales and employment, respectively, across 1-digit sectors according to NACE Rev. 2. Manufacturing, construction and services make up 99% percent of firms in the sample.

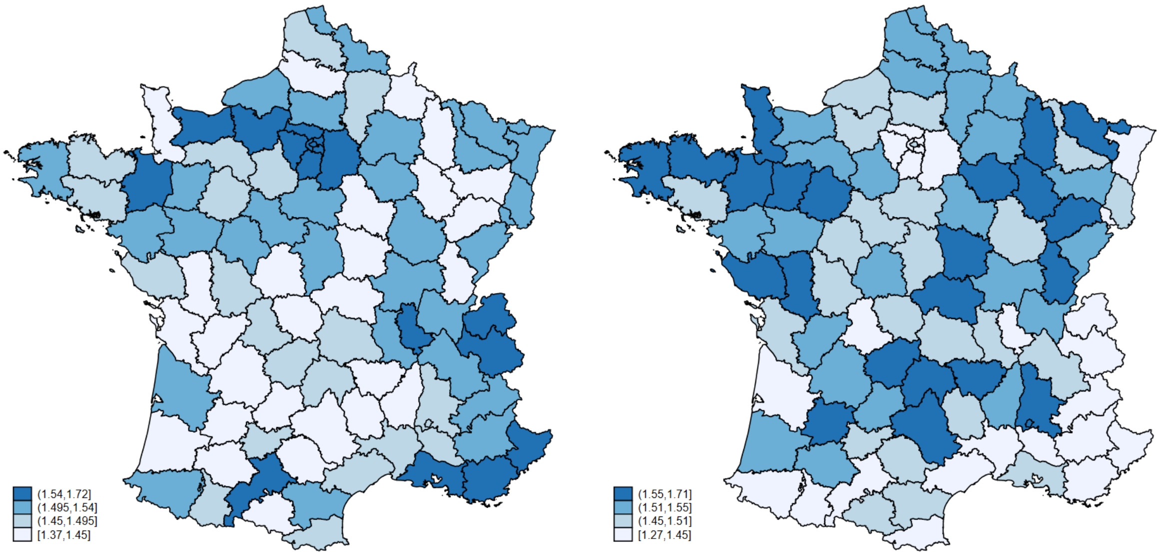
Wambach, 2021). With the availability of balance sheet data across a wide range of sectors, we are able to estimate both markups and markdowns across sectors based on a large coverage for France. Figure 2 shows the distribution of markups and markdowns across 1-digit NACE sectors. We see substantial variation in the weighted averages of markups and markdowns. As for the trends, we weigh markups based on output and markdowns based on employment.

Manufacturing, construction and services comprise nearly 100% of the full sample, while mining and quarrying and electricity, gas and water supply make up less than 1% of all observations in the final sample. In manufacturing, markups are somewhat lower than in construction and services, where markups are the largest on average. They are on average 1.75 in services, and around 1.78 in construction and 1.48 in manufacturing. Weighted markdowns, on the other hand, are the highest in manufacturing with around 1.78 and the service sector with values of around 1.61, while they are just below 1.4 in construction. In the small sectors, i.e. mining and quarrying and electricity, gas and water supply, average markups are around values of 2, and markdowns are above 1.7 as well.[14] This figure already shows that extending the analysis be-

[14]Given the large markups in the sector including electricity, we believe that, at least in the case of France, using materials compared to electricity is a better flexible input in the market power estimation.

yond a single sector is crucial in order to understand economy-wide developments and trends. Finally, we present the spatial distribution of market power in Figure 3, where the left panel shows markups and the right panel shows markdowns. They are weighted by output and employment, respectively. It is particularly interesting to compare this spatial distribution to Marinescu et al. (2021, Fig. 5), which present the degree of market power based on Herfindahl indices for the period 2011 until 2015. Differences can occur due to both the type of measurement, and the different time period, in particular due to the Great Financial Crisis between the two time periods. For example, due to increased exit and entry during and after the Great Financial Crisis, the geographic composition of markups and markdowns can change, even if the measure of firm market power was unchanged.

Figure 3: Geographic Distribution of Market Power



(a) Markups

(b) Markdowns

Notes: The maps show the spatial distribution of markups (left) and markdowns (right) in mainland France. The geographic allocation is based on the information on the "département" in the FICUS data.

Our maps of markups (left panel) and markdowns (right panel) exhibit that regions with high product market power do not coincide with regions with high labor market power. We find that average markups are larger in urban regions, whereas markdowns are larger in rural areas. Specifically, we find that markups are rather high in and around Paris, along the Mediterranean Coast and in Lyon, as well as in the départements encompassing Bordeaux and Toulouse in the Southwest of France. This is in contrast to Marinescu et al. (2021), who show that Herfindahl concentration indices are large in rural areas for product markets. This can be driven by the flaws of concentration indices as expressed by Syverson (2019) or the different time period. Interestingly, our measures of labor market power are substantially more similar to Marinescu et al. (2021), albeit minor differences exist with respect to the precise location. For example, Marinescu et al. (2021) and we find high labor market power in the less populated regions in the Northeast, Southwest and Northwest. In the area around Paris and along the Mediterranean Coast, we find low levels of labor market power.

Table C2 in the appendix describes the key variables in our final sample on the firm level and aggregated to the municipality level. The final sample includes all observations across all three measures of market power, i.e. Cobb-Douglas (both OLS and GMM) and Translog (GMM). The translog production function is our preferred measurement of market power. But as we combine all measures of market power in the final data set, and as the top and bottom two percentiles potentially affect different firms, we have slightly less observations for each measurement of product and labor market power than in the full sample, where all are combined. As Table C1 shows, our final sample is not representative of the French economy. That is why we weigh the observations in order to restore the sectoral composition of firms in the "cleaned and merged" data set. Essentially, we put more weight on service sector firms, and less weight on firms in manufacturing and construction.

Markups are larger than markdowns using the weights for sectoral composition only, which is in line with the trends shown above in Figure 1. Similarly, the average markdown for low-skilled workers is smaller than the average markdown for high-skilled labor. The summary statistics also reveal that we observe substantially less firms where both types of labor are working at the same time. Based on full-time equivalent employment, we observe nearly 2 million firm-year combinations, but when differentiating by skill we observe only slightly more than 450,000 firm-year combinations. Among those firms, where we observe both low- and high-skilled workers, the share of high-skilled workers is equal to 21%. Firm size in terms of full-time equivalent employment is close to 10, which is slightly larger than in previous samples. As explained above, this is a common issue in studies analyzing market power due to data availability issues for small firms. When we look at the sectoral composition, we can observe that they are equivalent to those in the "cleaned and merged" sample in Table C1, implying that our weighted sample is representative in terms of sectoral composition of the French economy. Specifically, the share of manufacturing firms is equal to 26%, the share of construction firms equal to 31% and service sector firms comprise 43% of all observations.

On the municipality-level, we have close to 250,000 observations in the sample out of a potential 396,286 observations if there was at least one firm by municipality in every year. The 250,000 observations comprise slightly more than 12% of the size of the firm-level sample. Therefore, it is not surprising that we observe 8.27 firms per municipality in a given year. However, firm size with respect to full-time equivalent employment is smaller in the municipality level data set: average size is 7.65 compared to 9.87 in the firm-level sample. The share of high-skill workers is 20%, implying that the average firms employs four low-skilled workers per high-skilled worker. This is similar to the firm-level data set. However, due to the aggregation, proportionally we lose less observations when distinguishing markdowns by skill level.

5 Empirical Assessment

5.1 The Impact of Broadband Internet on Markups

The impact of broadband internet on markups is ambiguous because both firms and consumers experience a reduction in information frictions with broadband internet. Higher price transparency for consumers reduces markups as prices should be closer to marginal costs. On the other hand, firms have various mechanisms how to increase markups, e.g. through expanding demand or supply chain management, and an imperfect pass-through of cost-savings to prices. Thus, it is an empirical question if one side profits more from the decline in information frictions than the other.

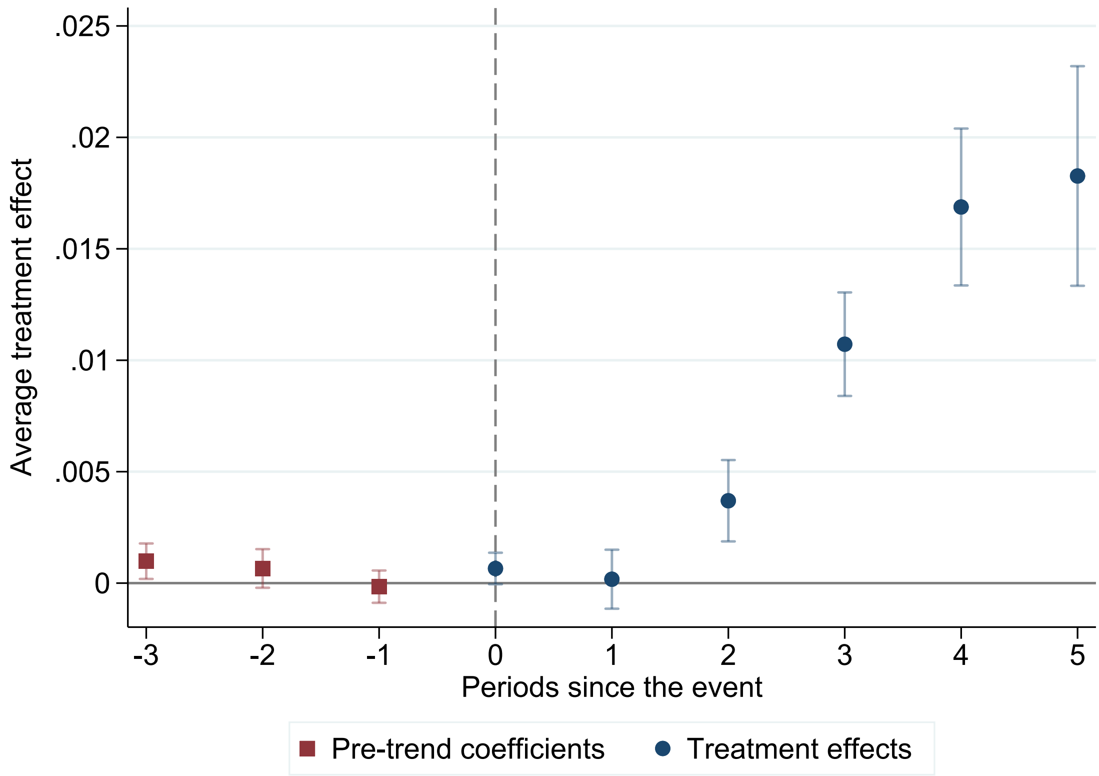
Figure 4 presents evidence that firm-level markups are increasing after the municipality where the firm is located is connected to broadband internet. The impact, however, is very small in the first two years after the introduction, and not always statistically significant. From three years onwards after obtaining access to broadband internet, this impact increases substantially and becomes economically meaningful. After five years, the markups increase by three percentage points. This indicates that in the first years there is a balance in terms of who profits from the reduction in information frictions, i.e. neither consumers nor firms see a dominant effect initially. However, this changes after three years after obtaining access to broadband internet, when the markups of firms increase and become economically meaningful.

5.1.1 Mechanisms

We test various mechanisms how firms can exploit the internet in order to charger higher markups. As we discussed them in more theoretical detail in Section 2, we focus here on the empirical side. In order to test various mechanisms, we assign indicator variables to firms whether they are more likely affected by a certain mechanisms or not. Empirically, we then estimate a triple difference-in-differences approach in order to test for the importance of the respective mechanism.

We start by testing the importance of increasing demand/geographic reach through two distinct mechanisms, namely rising exports and advertising. It is important to keep in mind that for expanding demand, either through exports or advertising, consumers should also be connected to fast internet. Given that the expansion of broadband internet was driven by population density in France, we believe that this is primarily the case. In order to measure whether a firm exports more with the internet, we have assigned all firms to be profiting from this channel if they experience an increase in their absolute real exports, i.e. accounted for sector-specific producer price indices. The data is taken directly from the FICUS data set. The balance sheet data, however, does not provide direct expenses for advertising. That is why we exploit input-output tables on the sector level. We rank the sectors which increased their relative input share

Figure 4: Internet Diffusion and Markups



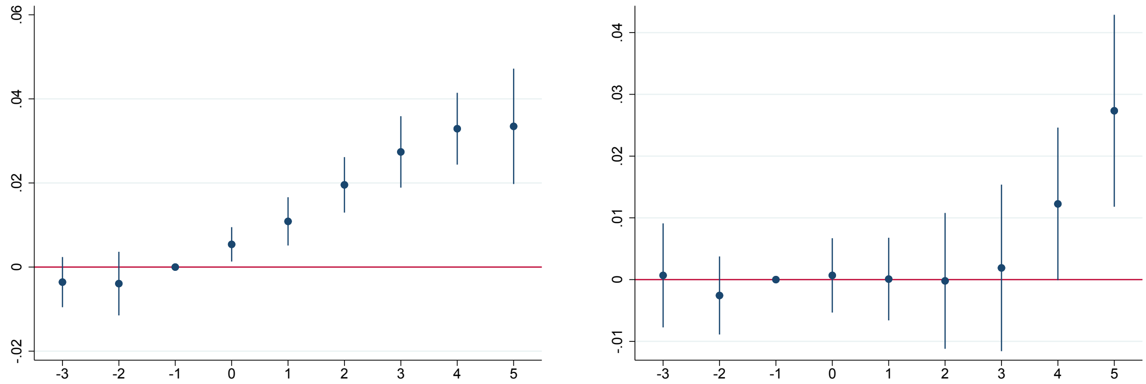
Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm product market power. The results are based on the difference-in-difference estimator by Callaway and Sant'Anna (2021).

from "Advertising and Market Research" between .[15] All firms belonging to the four sectors, which experience the strongest increase between 2000 and 2007 in advertising expenditure, are marked as profiting from this channel.

Figure 5 presents the results for the triple difference-in-differences estimation for expanding demand. The left panel displays the result for exports and the right panel presents the result for advertising. The graphs clearly show that the increase in exports is a key driver for the rise in markups. The baseline results indicate an increase of three percentage points increase in markups after five years, and exporting firms experience an increase by about 5.5 percentage points. Importantly, this increase in markups is very steady over time, but levels off slightly in the last three years after receiving access to broadband internet. This shows the importance of offering products and services more economically with greater geographical reach as pointed out by Boyer et al. (2002).

[15]Due to the coarseness of sectors in the input-output tables, it also includes "Other professional, scientific and technical activities, and veterinary services". However, we believe that they are unlikely to drive the rise over time given the growing importance of advertising.

Figure 5: Expanding Demand



(a) Exports

(b) Advertising

Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm product market power based on a triple difference-in-differences estimation. The triple difference relates to firms increasing their exports and their advertising in the right and left panel, respectively. Both mechanisms relate to an expansion in demand.

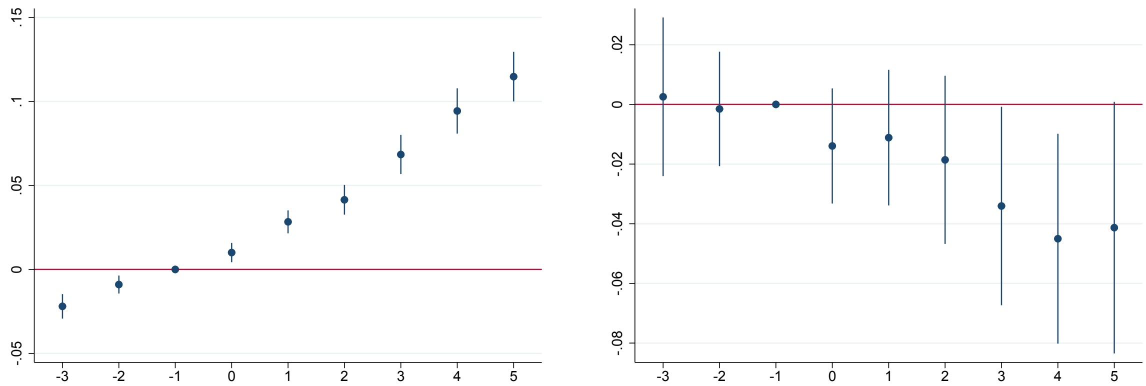
The right panel shows that advertising plays a much smaller role compared to exports. This holds both in terms of magnitude after five years as well as the time post treatment until we can see an effect on markups. After five years, the effect is slightly below three percentage point, and the effect is only statistically significant at the 10% level after four years. This shows that expanding demand through exports is substantially more important than advertising, and indicates the importance to consider the joint effect of globalization and technology and how they complement each other leading to an increase in markups.

Firms do not only use the internet to expand the demand for their products, they can also change the input composition in order to produce the same output at lower costs. Specifically, we investigate two types of supply chain management, namely in the form of imports (Malgouyres et al., 2021) and of domestic outsourcing (Bergeaud et al., 2022). We exploit the rise of China in global commodity markets in the early 2000s for three reasons: first, opposite to exports, imports are not specifically included in balance sheet data.[16]. Second, it coincides largely with the expansion of broadband internet - China joined the WTO in late 2001 - , and third, China provides many cheap, labor-intensive manufacturing inputs. We again use the input-output tables and calculate the average share over 13 manufacturing inputs across all industries between 1996 and 2000. We then use trade data from WITS (World Integrated Trades Solutions) by the World Bank in order to compute the growth rate by manufacturing input between 2000 and 2006. We then compute the rank of industries exposed to China based on the initial input composition and the rise of French imports from China. We assume that all firms in the four most-exposed sectors are subject to this import shock.

[16]Even if they were, it is questionable if they are useful given that quantities are typically not included, but instead reflect a linear combination of quantities and prices

With respect to (domestic) outsourcing, we exploit the change in outsourceable occupations over time at the firm level. Firms that decreased the employment share (measured in work hours) of outsourceable occupations are assigned to make use of this mechanism. In the definition of outsourceable occupations, we follow Bergeaud et al. (2022), which include - among others - IT engineers, IT technicians, HR executives and security guards, cleaners and road drivers.[17] One key issue is that these occupations are experiencing an overall increase in the French economy, therefore not many firms are part of the group, where we categorize as applying the mechanism of (domestic) outsourcing.

Figure 6: Supply Chain Management



(a) Chinese Imports

(b) Outsourcing

Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm product market power based on a triple difference-in-differences estimation. The triple difference relates to firms increasing their imports from China and their (domestic) outsourcing in the right and left panel, respectively. Both mechanisms relate to supply chain management.

Figure 6 displays the results for the triple difference-in-differences estimation for supply chain management, i.e. imports from China in the left panel and (domestic) outsourcing in the right panel. In comparison, Chinese imports play a substantially more important role both in terms of speed of an economically meaningful effect, as well as the magnitude of the effect. After five years, the impact is around 11.5 percentage points, and thus outperforming the baseline estimate for the full sample by a factor of nearly four. This also means that it is the single most important mechanism for the overall impact of broadband internet on markups. Further, this reinforces the importance to consider the joint effect of globalization and technology on economic outcomes.

The right panel shows that outsourcing plays essentially no role with respect to markups. The effect is only statistically significant at the 10% level after five years, but before is always close to zero before. Given the large confidence interval in the final period, the last period can be

[17]For a full list, see Table XY in the appendix. It also provides a distinction between low- and high-skill outsourcing occupations.

easily due to selection effects as we do not observe many firms five years after treatment. This shows that, while firms invest fast in domestic outsourcing after the obtaining access to broadband internet (Bergeaud et al., 2022), this does not have an immediate effect on markups due to labor cost savings.

5.1.2 Superstar Firms

A recent literature highlights the importance of "superstar" firms driving the increase in average markups (Autor et al., 2020; De Loecker et al., 2020). Specifically, superstar firms are defined as the most productive firms. We therefore divide our firm sample into four quartiles based on proxies for productivity. Specifically, we use value added and value added over employment as proxies. We then estimate a triple difference-in-differences comparing which firms in the productivity distribution profit most from gaining access to broadband internet. As a baseline category, we use the first quartile, i.e. the least productive firms in our sample according to value added and value added over employment.

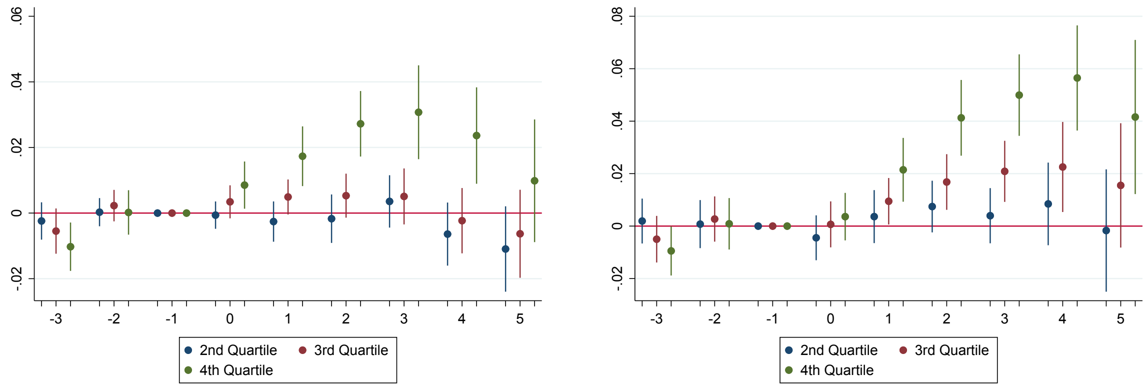
Figure 7 provides evidence that the most productive and largest firms profit the most from the expansion of broadband internet in terms of markups. Both graphs indicate an increase in markups after the municipality a firm is located in gets access to broadband internet. In both panels, the coefficients five years after the introduction of broadband internet are around .02, implying that the most productive firms increase their markups by two percentage points more than the least productive firms. However, the last two coefficients in the right panel are estimated with noise. On the other hand, firms in the second and third quartile increase their markups less than the least productive firms, i.e. our baseline category. Both graphs provide evidence that they increase their markups between one and two percentage points less than the bottom quartile with respect to productivity.

It is important to combine this finding with the importance of globalization from the previous subsection, both in terms of cheaper imports and exporting more. Taken together, these results imply that the most productive firms which manage to use the new technology to their benefit, are the main drivers of rising markups in the French economy. In short, productive firms are making the best use of the exploiting the combined effect of technology and its ability to profit stronger from globalization.

5.2 Markdowns

We now investigate the impact of broadband internet on labor market power that firms exert over employees. In theory, both firms and workers profit from the reduction in a decline in information frictions on the labor market: on the worker side, broadband internet raises information about outside options for workers, both relating to employment itself as well as the wage. But technology can also increase markdowns through a lower number of employers and a lower willingness to renegotiate wages.

Figure 7: Superstar Firms



(a) Value Added (b) Employment

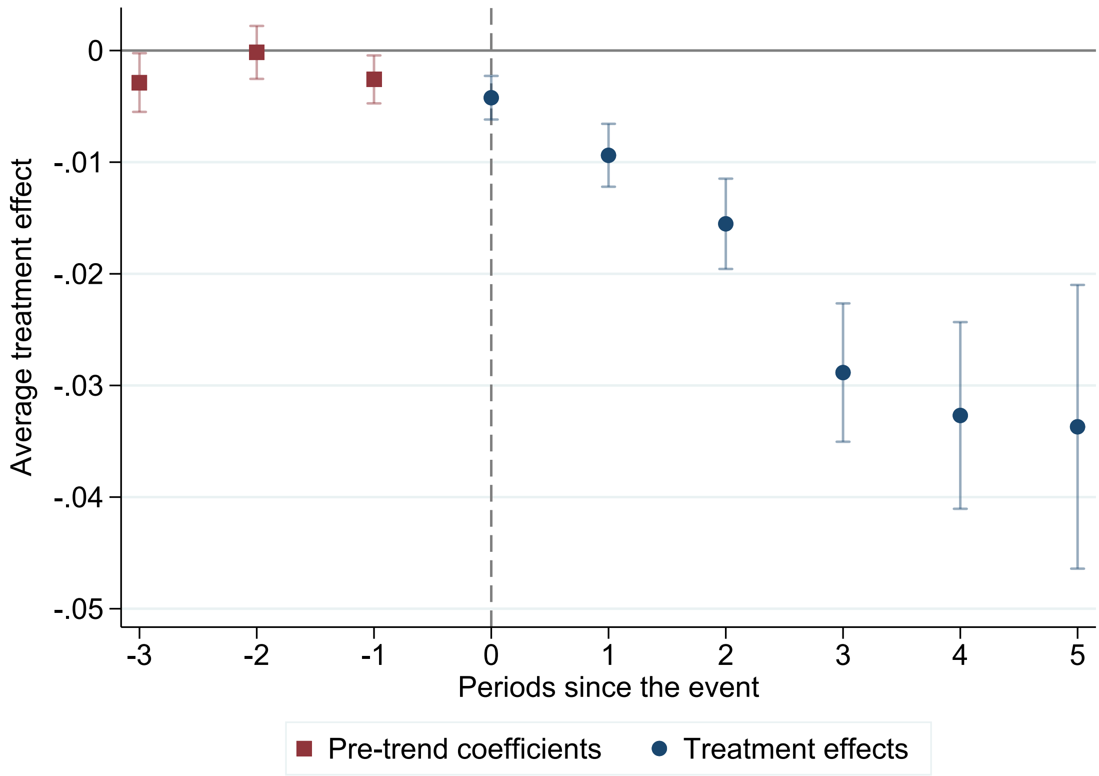
Notes: This figure shows the estimation results for a triple difference-in-differences estimation, where firms within the first quartile of the value added and the size distribution serve as a benchmark category, respectively. It compares how markups change for the other three quartiles relative to the lowest quartile of the distribution.

Figure 8 shows that firm-level markdowns are decreasing after the municipality where the firm is located is connected to broadband internet. The impact is immediate and increases over time. The magnitude on impact is below one percentage point, but significant at all conventional levels. Five years after the introduction of broadband internet, the impact is slightly above two percentage points. This finding speaks to the improvement for workers due to lower information frictions as workers learn about outside options with respect to both employment and wages. That is how broadband internet can reduce the impact of firm's market power in the labor market.

In terms of magnitude, the point estimate is slightly smaller than the (absolute) magnitude of the impact of broadband internet on markups in Figure 4 after five years. However, the immediate impact is stronger for markdowns than for markups. This implies that total firm market power, i.e. the product between labor market and product market power, has not changed substantially due to access to broadband internet, but it is important to consider who is affected. While workers profit from reduced markdowns, both workers and non-workers (unemployed and non-labor force participants) are affected negatively by increasing markups. Therefore, the overall welfare effect is not clear and is likely to depend on the share of workers relative to the population.

Given previous findings that internet increases labor productivity, we will focus on wages. However, we also provide evidence in Figure D1 that wages are actually increasing after access to broadband internet. We do so both at the firm level using the overall wage bill, and at the worker-level using

Figure 8: Internet Diffusion and Markdowns



Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm labor market power. The results are based on the difference-in-difference estimator by Callaway and Sant'Anna (2021).

5.2.1 Mechanisms

In order to understand the underlying mechanisms, we start by investigating whether the internet helps to increase wages due to its effect on worker representation. The internet can facilitate both the reach of worker representation through wider reach as well as better communication. In both cases, the bargaining position of employees through worker representatives improves, which in turn helps to demand higher wages, and thus reduce markdowns.

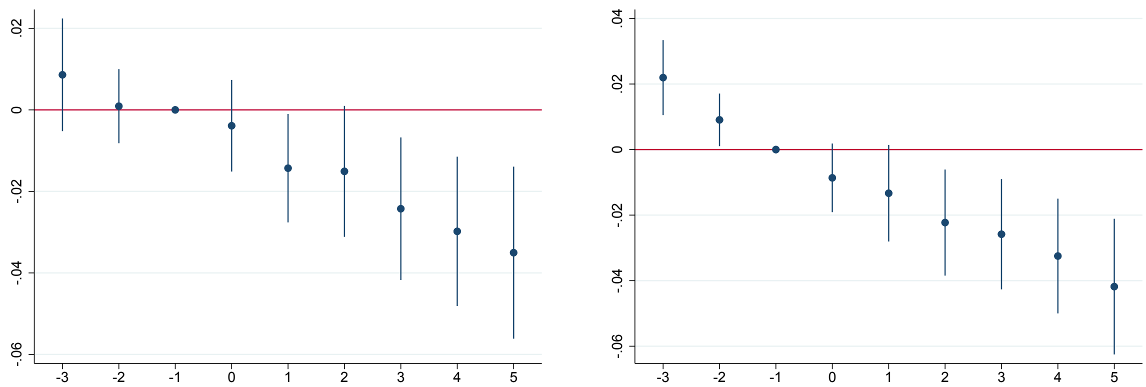
We measure the degree of worker representation using the REPONSE (RElations PrOfessionnelles et NégociationS d'Entreprise) survey, specifically from the 1998/1999 survey wave. We use this wave because it is the last wave preceding the introduction of broadband internet in France. We exploit the survey of senior managers, who answer the questions in face-to-face interviews. The data has been used by Caroli and Van Reenen (2001) and Fairris and Askenazy (2010).[18] We collect information on the presence of a trade union in the enterprise and on whether a work council is present in the establishment. We then aggregate the information to

[18]Marinescu et al. (2021) use the REPONSE survey of employees in the year of 2011, which contains more information on union status.

the sectoral level using the weights provided by the survey. Ultimately, we choose the twenty sectors with the best representation of employees in the form of trade unions or work councils, which corresponds to around 10% of the firms in our sample.

Figure 9 provides evidence that the internet indeed helped worker representatives to bargain higher wages. This can be due to union revitalization with the help of the internet as discussed in Pliskin et al. (1997), Diamond and Freeman (2002). Further, Martínez Lucio (2003) discusses various strategies how unions, or worker representatives in general, can respond to internet access: communication strategies, changing union identity and different forms of internal democracy. The left panel shows the results for unions, and the right panel for worker councils. In both cases, we can see a clear decline in markdowns for firms where worker representation is high following the introduction of broadband internet. The impact in magnitude is larger for work councils with a coefficient of -.042 in the fifth year after broadband internet access, compared to -.34 for unions.

Figure 9: Worker Representation

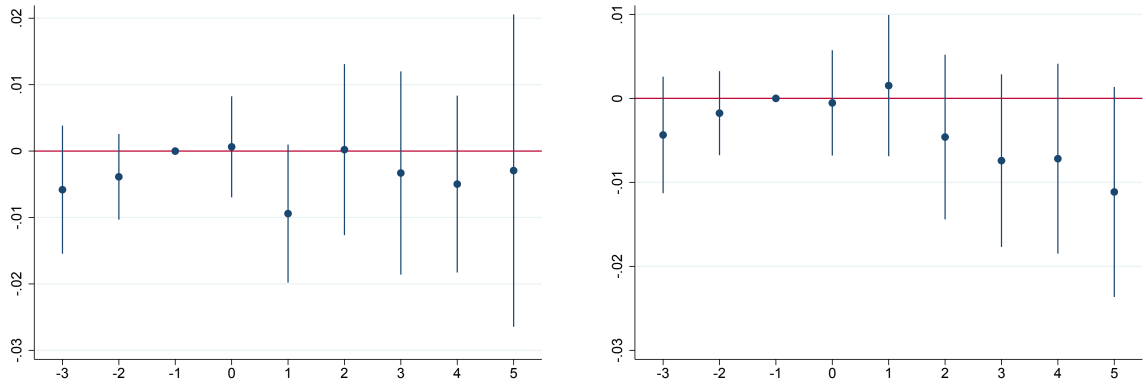


(a) Unions (b) Work Councils

Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm labor market power based on a triple difference-in-differences estimation. The triple difference relates to firms in sectors, where trade unions and worker councils are present, respectively, i.e. where worker representation is strong.

In Figure 10, we test two further mechanisms. First, we examine whether labor market tightness in the commuting zone, where the firm is located, in 1999, i.e. before the roll-out of broadband internet. We choose firms in the commuting zones with the highest labor market tightness, specifically those from the top decile. We take the data from the "Statistiques Mensuelles du Marché du Travail", which is collected by the public employment service (Pôle Emploi). The left panel shows that markdowns are not declining significantly more for firms in tight labor markets. Second, we investigate the importance of the minimum wage because the internet may help workers to learn about the current level of the minimum wage, as well as report potential abuses. We choose firms that employ at least 20% of its workforce with workers earning below the minimum wage of the subsequent year in at least half of the periods that we observe the firm in our final data set. Around 10% of firms qualify under these restrictions, but the right panel does not indicate a significant effect, albeit markdowns tend to decline more in firms that rely more on workers earning close to the minimum wage.

Figure 10: Labor Market Tightness and Minimum Wage



(a) Labor Market Tightness (b) Minimum Wage

Notes: This figure shows the regression coefficients and the 95% confidence intervals for the impact of broadband internet roll-out on firm labor market power based on a triple difference-in-differences estimation. The triple difference relates to firms increasing the labor market tightness in the commuting zone and whether they employ a large share of workers earn below the minimum wage of the subsequent year, respectively.

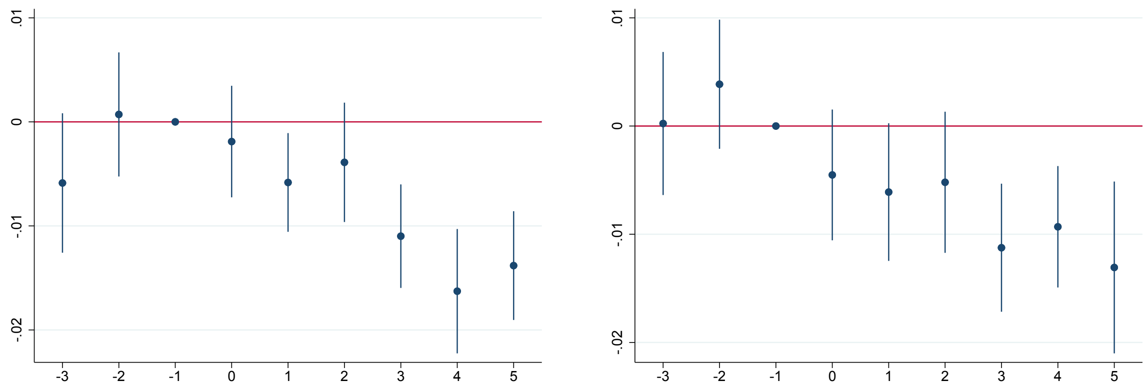
5.2.2 Skill Bias

As with most technological advances, broadband internet can have a skill bias, i.e. workers along the skill distribution are affected differently. However, in theory broadband internet has different positive effects on low- and high-skilled workers, and therefore the skill bias is ambiguous. Yet, Akerman et al. (2015), Bergeaud et al. (2022) and Atasoy (2013) all report findings that are consistent with skill bias in favor of high-skilled workers due to the expansion of broadband internet. But there is also evidence that low-skill workers profit, e.g. from better labor market matching in the form of longer tenure and higher entry-level wages due to higher labor demand (Bhuller et al., 2019).

The first approach to understand type of skill bias is to use worker-level evidence on wages. To this end, we make use of the EDP (Echantillon Démographique Permanent), which is a subsample of the panel DADS. The key advantage over the panel DADS is that it contains individual information on worker education from the 1999 census. Before 2001, the EDP panel covers all individuals born the 1st, 2nd, 3rd, or 4th of October, and since then it includes all workers born one of the four first days of a quarter. We can link the introduction of broadband internet to the municipality of residence of workers. Besides the same data procedure for firms described in Appendix C, we focus on workers that change their employer at most once between 1997 and

2007. This is allows us to better differentiate between job stayers and movers, and specifically on the wage effect of the single job change.
Figure 11 shows the results for regression wage (growth) on the arrival of broadband internet interacted with a dummy for skill, which takes on the value one if the individual is high-skilled. We apply two classifications of skill, one is based on occupational classification and the other on educational attainment. While the EDP contains occupational codes for all observations, it does only contain educational information based on the 1999 census for half of the observations. Based on occupational codes, we define high-skilled workers as CEOs or small-business owners and high-paid professionals (CS codes 2 and 3). When using the educational codes, we define workers with at least an undergraduate degree as high-skilled. Independent of the classification, it indicates that wage growth is weaker for high-skill workers, or - in other words - stronger for low-skill workers.

Figure 11: Skill Bias at the Worker Level



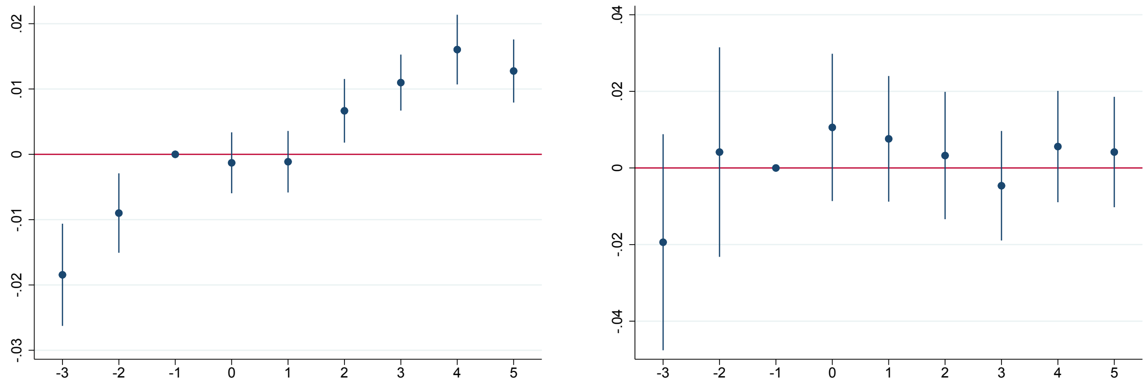
(a) Occupational Classification

(b) Educational Classification

Notes: This figure shows the estimation results for a triple difference-in-differences estimation, where we regress wages on the arrival of broadband internet interacted with skill level using the EDP.

In Figure 12, we investigate whether changing employer drives our results of a "reverse" skill bias. To do so, we interact the arrival of broadband internet interacted with changing the employer and run the regression separately by skill levels. Here, we use the definition of skill based on occupational classification. In this sample, we only keep workers that change their employer only once in order to have a clearer picture before and after the change. The left panel reveals that changing employers is driving the wage growth of low-skill workers due to the arrival of broadband internet. At the same time, changing the employer for high-skilled individuals does not have a significant impact on wages. However, in both cases, the pre-trend is below zero, which might be explained by the fact that workers changing their employer are working initially in bad employers, which might induce them to change the employer. In Appendix D, we provide evidence that this result also holds when using educational classification of skill for a smaller sample.

Figure 12: Changing Employer by Skill



(a) Low-Skill

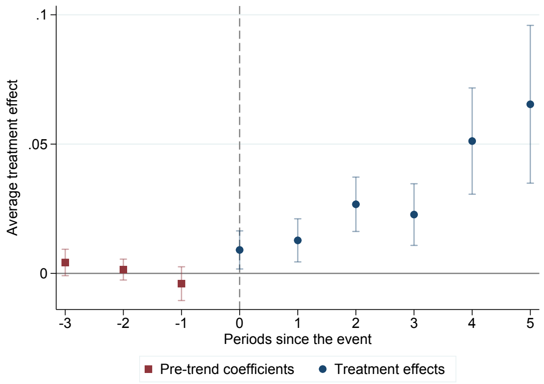
(b) Educational Classification

Notes: This figure shows the estimation results for a triple difference-in-differences estimation, where we regress wages on the arrival of broadband internet interacted with changing the employer. It is based on data from the EDP, and we keep only workers who changed their employer at most once during the sample period. We run the regression separately by skill skill level based on occupational classification.

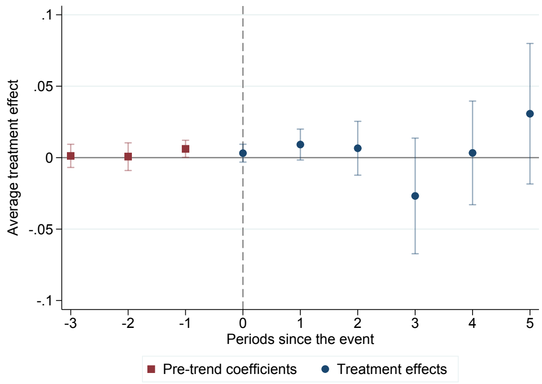
The second approach how we intend to determine the impact of broadband diffusion on markdowns by skill is to estimate markdowns by skill group based on the procedure we explain in Section 3. To do so, we differentiate by the occupational level of workers based on information from the DADS. We define the skill-level of workers based on one-digit occupational codes: We define high-skilled workers as CEOs or small-business owners and high-paid professionals (CS codes 2 and 3), while we denote intermediate professions, low-paid employees and blue-collar workers (CS codes 4 to 6) as low-skill workers. We want to highlight that the firms, which employ both low- and high-skilled workers in our sample is not representative of the sample, and typically include large firms. Further, we only drop firms where the expenditure share for each type of labor only exceeds 5% because the sample of firms for which we can calculate markdowns for both skill levels is smaller and even more biased.
Figure 13 shows how markdowns differ after the introduction of broadband internet by skill type. The left panel shows the evolution of markdowns for low-skill workers, and the right panel for high-skill workers. Due to the selection bias (large firms are overrepresented in this sample), markdowns are not declining for either type of workers. However, we find a clear difference in the evolution of markdowns by skill type: markdowns are unchanged for high-skill workers, whereas markdowns are increasing for low-skilled workers. This finding implies that the expansion of broadband internet carries a skill bias as found in previous work (Akerman et al., 2015; Bergeaud et al., 2022), at least in large firms.

These conflicting findings indicate that the skill bias of broadband internet maybe not be uniform across the firm distribution. Another reason may be that large firms, for which we find the skill bias in line with the previous literature, are capable of paying low wages for low-

Figure 13: Skill Bias at the Firm Level



(a) Low-Skill Employment



(b) High-Skill Employment

Notes: This figure shows the estimation results for a triple difference-in-differences estimation, where .

skilled workers relative to their marginal revenue product of labor, but the wages are still larger for low-skill workers in firms where their marginal revenue product of labor was not as high.

5.3 What can we say about welfare?

Did public investment in broadband internet increase overall welfare in the economy? Our findings indicate that markups are increasing and markdowns are falling due to the introduction of broadband internet in mainland France during the early 2000s. While a decline in labor market power is unambiguously positive for welfare, an increase in markups can dampen this positive effect, and potentially reverse it. However, in our case, where markups are likely driven by cost savings (cheaper intermediate inputs, larger customer base and better communication possibilities), the question how a rise in markups affects welfare is ambiguous itself.

In the standard (static) monopoly model with downward sloping demand and marginal revenue curves and convex marginal cost and average total cost curves, our findings imply two shifts.[19] First, an increase in markups shifts the marginal cost curve downwards, and hence also the average cost curve. Second, the demand curve shifts to the right, and with it the marginal revenue curve. For simplicity, we assume that there is no change in the elasticity of demand due to the decline in markdowns. Then both shifts imply that consumer surplus, producer surplus as well as deadweight loss increase in absolute magnitude. The proportions depend on the actual shapes of all functions, in particular on the elasticity of demand and the marginal cost curve.

However, if we go beyond the static model, the welfare implications are more complicated. The decline in labor market power of employers is unambiguously positive in terms of consumer

[19]We assume standard shapes of the curves, i.e. straight downward-sloping demand and marginal revenue curves, an inverted u-shape for the average total cost curve, and marginal costs that are initially declining slightly and increasing strongly with quantity.

welfare, also in dynamic settings. For example, Berger et al. (2022) show that labor market power in the United States implies a decline of 6 percent of lifetime consumption compared to the efficient allocation. But with respect to the increase in markups, the welfare implications are not clear. First, Berry et al. (2019) argue that welfare effects are ambiguous if markups are increasing due to cost reductions. Specifically, the decline in marginal costs may be due to a shift towards fixed (or sunk) costs. This is quite likely in our case, as (fast) internet connections make investments in networks, product quality and diverse geographic locations more attractive. In this case, observed higher markups may or may not be associated with higher prices and reduced consumer welfare. Importantly, changes in quality and fixed costs have to be considered. For example, Grieco et al. (2022) find that consumers profit from better quality and improved production technology. At the same time, Ganapati (2021) finds for the wholesaling sector that concentration and markups are increasing, but quality and costs are falling. Hence, it is not easy to evaluate consumer welfare in this market.

Increasing markups can have further adverse advantages for three reasons: misallocation, distributional consequences and the direction of technological change. First, Edmond et al. (2023) argue that markups incur costs to society through three channels, namely an aggregate markup acting like a uniform output tax, misallocation of factors due to the cross-sectional dispersion of markups, and inefficient entry.[20] Second, Boar and Midrigan (2019) highlight the potential of distributional costs if firm ownership is concentrated at the top of the income distribution. Han and Pyun (2021) present a positive link between rising markups and income inequality, which is particularly driven by the very top. Specifically for France, Auray et al. (2022) corroborate this finding and show that the increase in markups is the main culprit of rising income inequality.[21] Third, Acemoglu (2023) argues that high-markup sectors and technologies attract more innovation, which leads to a potential distortion of research activity. If these sectors are not maximizing the social objective, then the distortions lead to welfare-reducing direction of innovation. He discusses the distortion in particular with respect to industrial automation, the health care sector and energy. Similarly, Aghion et al. (2022) argue that the social planner intervenes if markups are due to a higher process efficiency than competing firms. In this case, the social planner reallocates research resources away from high-markup firms due to the distortionary effect. The negative effects of market power in dynamic settings could be offset by the increase in product variety. In the standard Dixit-Stiglitz framework of monopolistic competition, love for product variety is inherent in consumers' preferences through a CES utility function. Brynjolfsson et al. (2003) provide evidence that the internet increases product variety because it enables online retailers to catalog, recommend, and provide a large number of products for sale. Further, Gentzkow and Shapiro (2011) show that online news consumption is more varied than offline news consumption. However, there is also recent evidence that online retailers are

[20] The authors argue that the entry channel is the least important, whereas the other two channels are the key drivers behind the cost of markups.

[21] Eggertsson et al. (2021) argue that wealth inequality also increases due to rising markups as they increase stock prices, and high-wealth individuals tend to hold proportionally more wealth in equities.

abusing their market power (Farronato et al., 2023), which in turn can reduce the number of firms in the market and thus the quality of new products.

Given the high dimensionality of mechanisms on welfare implications, it is very hard to say how broadband internet access affects consumer welfare. This holds for specific markets and for the aggregate economy. Ultimately, it will depend on various parameterizations, such as elasticity of demand, love for variety as well as the degree of pass-through of cost-savings from firms to consumers. Even with these parameters, it is difficult to determine welfare effects of broadband internet given the dynamic effects of rising markups.

6 Sensitivity Analyses

We start with an the estimation of both markups and markdowns. Specifically, we discuss various results, such as the production function parameters, the extension to skilled and unskilled employment and accounting for labor adjustment costs, which are potentially more important in the French labor market compared to other labor markets. In the second part, we examine the robustness of our difference-in-differences estimation. In particular, we test whether our results hold with alternative measures of markups and markdowns, i.e. based on a Cobb-Douglas production function, and on the municipality level.

6.1 Estimating Markups and Markdowns

6.1.1 Market Power Estimation Results

In Appendix B we provide an overview of the number of observations by two-digit sector, estimation results for the production function parameters used to compute output elasticities and some robustness analyses. Table B1 provides an overview of the NACE two-digit sectors including the digit and the sector name. We complement the information with the number of total observations and the number of distinct firms we observe for a given sector. After excluding agriculture, finance and insurance sectors and the public sector, NACE contains 67 two-digit subsectors, of which we cover 55. We lose four sectors in “Mining and Quarrying”, two in “Manufacturing”, two in “Water supply; sewerage, waste management and remediation activities”, three in “Transportation and storage” and one in “Information and communication”. These losses are primarily due to the requirement of observing at least 1,000 observations per two-digit sector.

In Table B2 we show the results for production function parameters by sector. All squared terms for labor, materials and capital are always positive, while the constitutive terms are often positive, but sometimes exhibit negative signs, in particular for materials we observe negative signs. Interestingly, the interaction terms primarily exhibit negative signs with very few exceptions. The magnitude of the coefficients of the interaction terms involving labor are the largest, both the constitutive and the squared terms with averages of .8 and .1, respectively. However, the two interaction terms including labor also are on average more negative than the interaction term between materials and capital. The constitutive term of materials is slightly below zero, but the production function parameter of the squared term is larger than .06 on average. For capital, the constitutive term is slightly larger than .06, but the squared term is just below .024. We re-estimate the production function parameters for two different periods in order to determine whether production technology changes substantially over time. We show the differences between the production function parameters between the period of 1996 until 2001 and 2002 until 2007 in Table B3. On average, the squared terms hardly change between to two time periods, but the constitutive terms change slightly. The parameter for labor falls slightly over time by .026, and the parameters for materials and capital rise by .012 and .013, respectively. However, for some sectors, there are more substantial changes in the production function parameters, but larger changes in constitutive terms are offset by changes in interaction terms. For example, the correlation of the change in the constitutive term for labor exhibits negative correlations with the interaction terms including labor: the correlation between the change in constitutive term and the change in the interaction term with materials is equal to -.31, and the correlation between the change in constitutive term and the change in the interaction term with capital is equal to -.72. Further, the sectors where we observe larger changes in sectors with less observations, where the problem by splitting the full sample in two periods is exacerbated compared to large sectors.

Because of the potential in skill-bias in technology, we estimate markdowns by skill for a small subset of firms. Compared to the sample, where we simply take total full-time equivalent employment, for this exercise we require firms to employ both low- and high-skill workers at the same time.[22] That is why we observe fewer sectors, in particular we lose sectors 35, 37, 61 and 78. By separating labor into two separate inputs, our vector of production function parameters increases from 9 to 14 rows. In Table B4 we show the parameters by sector, where u indicates unskilled/low-skill labor and s denotes skilled/high-skill labor, while the other subscripts do not change. On average, the parameters for low-skill labor are larger than for high-skill labor, i.e. both the constitutive and the squared terms.

Lastly, we examine the importance of labor adjustment costs for markdowns in France, which is often considered as a more rigid labor market overall (Card et al., 1999; Siebert, 1997). In the baseline specification we assume the absence of labor adjustment cost. However, they can drive a wedge between the output elasticity of labor and its expenditure share. Consequentially, this can lead to an upward bias in our measurement of markdowns. We follow Yeh et al. (2022) and conduct two different robustness checks, one based on quadratic adjustment costs (Hall, 2004; Cooper et al., 2007) and one on non-convex adjustment costs. For the former, we apply the correction term developed by Yeh et al. (2022, Eq. 34), which exploits the plant's growth rates in employment and the wage bill and a parameter governing the magnitude of adjustment costs. For the latter, i.e. non-convex adjustment costs, we re-estimate the production function

[22]This requirement is on top of the other data requirements we explain below in Section 4.

parameters based on biennial data. The idea behind the biennial estimation is that adjustment costs matter less and therefore do not show up in this estimation.
We show the results from these robustness analyses in Figure B1, where we contrast each robustness measure with the baseline markdowns by sector, and in Table B5 we provide the exact estimates of markdowns. The left panel of Figure B1 contrasts our benchmark measure of markdowns with the measure including the correction term for quadratic adjustment costs. We can see that there is a very strong correlation between the two measures, and that the magnitudes are very similar as the values are very close to the 45-degree line. In the right panel we plot our benchmark estimates of markdown against markdowns with non-convex adjustment costs based on biennial estimation. With one exception, all sectors are very close to the 45-degree line as well.[23] The averages, weighted by firm level employment, also do not exhibit strong differences, with 1.66 for our benchmark analysis, 1.65 when accounting for quadratic adjustment cost and 1.61 when accounting for non-convex adjustment cost.

6.1.2 Discussion of the Underlying Assumptions

We want to address some criticism towards the validity of our measurement of markups and markdowns in this section. The first criticism is related to the choice of flexible input. Specifically, the "proxy variable approach" requires at least one flexible input, which typically has been labor since the work by De Loecker and Warzynski (2012), but the authors argue, as well as Basu (1995), that material inputs are flexible. While we believe that materials as a flexible input is not questionable, the important assumption by Yeh et al. (2022) is that there is no market power in this input market.
Morlacco (2019) shows that there is market power in imported intermediate inputs under the assumption that the market for intermediate inputs from the same country is perfectly competitive. If the ratio for markdowns is contaminated with market power in intermediate inputs, then we would overestimate the degree of labor market power. Specifically, it would reflect the markdown for labor relative to the markdown for materials. In order for our results to be meaningful, the following assumption needs to hold: the degree of firm's labor market power of a firm is unrelated to the market power of its material suppliers. If this assumption holds, then the distribution of markdowns is simply shifted towards the left compared to the true firm labor market power, and thus would have no influence on our estimates.
An alternative flexible input in the estimation of markups and markdowns is energy. For example, Kim (2017) argues that energy is less subject to market power due to stronger regulation of energy markets. However, Davis et al. (2013) presents evidence that the energy market is not perfectly competitive. Further, we show below that markups estimated for electricity, gas and water supply are very high (close to 2.5). Finally, energy expenditure typically makes up a small component of overall expenditure. Therefore, slight measurement error in a small expenditure

[23] The exception is sector 24, i.e. the manufacture of basic metals.

share can become very tangible regarding equations (2) and (3). These properties of energy as flexible input make us believe that materials are better suited for our estimation of markups and markdowns.

Most prominently, Bond et al. (2021) formulate critique towards the “proxy variable approach”. A key criticism, however, does not hold in our case. We have data on output, which is defined as “sold production of goods and services, production stored by the company and capitalized production, as well as the sales margin (sales of goods minus purchases of goods”. Therefore we do not need to proxy it with revenues, with which our estimates of markups would be downward-biased (Klette and Griliches, 1996). This also extends to markdowns, for which the issue is less relevant as Yeh et al. (2022) note. As the markdown in equation (3) includes a ratio of output elasticities, the bias cancels out and therefore does not apply.

The second key criticism relates to the use of inputs for non-production, but affect the quantity of output. For example, labor relating to marketing and advertisement can be used to increase demand of the firm’s products. We believe that materials are unlikely to be used to influence demand, as they typically encompass raw materials, pre-produced parts and supplies. If materials are not responsible for increasing demand, then our markups are not biased. With respect to markdowns, where we also exploit labor as a flexible input, it might be less clear. However, only .09 % of the workforce in the DADS are working in marketing or advertisement.[24] Hence, we believe that this is not a key driver of our estimates of markdowns.

The third and final key criticism by Bond et al. (2021) relates to the scalar observable assumption, i.e. that flexible inputs are chosen statically. The authors provide evidence that this assumption cannot be fulfilled as the econometrician would also need to observe a plant’s marginal cost of production (in the presence of market power). They suggest to use production function estimators that do not rely on this assumption, e.g. dynamic panel IV methods (Blundell and Bond, 2000). Yeh et al. (2022) adopt a data-generating process from Ackerberg et al. (2015), and using Monte Carlo simulations show that the violation of the scalar unobservable assumption does not pose significant problems.

6.1.3 Market Power Measures versus Concentration Indices

After discussing some of the drawbacks of the estimation procedure to measure markups and markdowns, we want to highlight some advantages of these measures and compare them to drawbacks of concentration indies still used in the recent labor market literature, among others Barkai (2020), Benmelech et al. (2020) and Marinescu et al. (2021).[25]

In our opinion, measuring markups and markdowns is closer to definition of firm market power, given that one standard definition is that a firm produces and sells goods and services with the

[24]Potentially, workers in advertising and marketing are captured in other categories. If we account for all workers in these categories as well, we observe 4% of workers potentially working in marketing and advertisement.

[25]For more papers using concentration indices for product and labor market power, see Berry et al. (2019).

aim of generating revenue and making a profit.[26] Markups relate to price-setting power for the output, while markdowns relate to wage-setting power of firms, which directly relate to the profits they earn. On the other hand, concentration is an equilibrium outcome, which Syverson (2019) calls the "deepest conceptual" problem. Specifically, he argues that concentration is driven by the interaction of both the nature of industry competition and other demand and supply conditions. He concludes therefore that concentration indices are potentially *worse than just a noisy parameter*. Similarly, Yeh et al. (2022) caution against using concentration ratios in employment to measure labor market power due to their weak link and dissimilar evolution over time.

Besides the key conceptual flaw, there are two more aspects why concentration indices are heavily criticized and not used anymore in the industrial organization literature. The first one relates to the underlying class of models, on which studies using concentration indices are relying. Specifically, they rely on the standard Cournot oligopoly model (Syverson, 2019) instead of Bertrand competition. The Cournot model implies a positive relationship between market concentration and average market power. This is because each firm has to consider less competitors' responses. Thus, it has the ability to both increase the price above average cost and reduce the wage compared to the marginal revenue product of labor.

However, a large class of models based on Bertrand competition predict a positive relationship between competition and concentration (Melitz, 2003; Asplund and Nocke, 2006). These models involve heterogeneous-cost firms selling differentiated goods.[27] In this type of model, more substitutability (consumers shift more easily between producers) implies that firm's residual demand curves are more elastic, hence price-cost margins are lower. At the same time, the increase in substitutability makes it more likely for high-cost firms to exit the market. That is why these models imply a positive relationship between competition (lower price-cost margins) and concentration (fewer firms). In light of different model predictions between the sign of the relationship, we are wary of the use of concentration indices and their actual relationship with market power. This holds in particular true as the model assumptions in Bertrand models seem more realistic over a large number of industries compared to the Cournot assumptions.

The second aspect of criticism of concentration indices relates to the definition of economic markets in order to measure concentration (Syverson, 2019; Berry et al., 2019). This criticism holds under all circumstances, even if the last two critiques of Herfindahl indices are not valid. Specifically, this relates to the scope of economics markets, where markets operate. In our case, this is particularly related to where firms sell their output and from which geographic area they draw their labor force. Typically, studies using concentration indices draw on some classifications of industries or occupations, and geographic units. With respect to the latter, it can be difficult in the face of nationally and locally operating firms (Rossi-Hansberg et al., 2021;

[26] More related to markups is the definition by Pindyck and Rubinfeld (2012) where the definition indicates that firms have the ability to influence the price at which it sells its products.

[27] In fact, Bresnahan (1989) shows that with differentiated products the negative relationship between concentration and market power breaks down.

Rinz, 2022). Finally, we believe that the introduction of the internet fundamentally shifts the geographic boundaries of both product markets and labor markets, making them unsuitable in our analysis.

Estimating markups and markdowns on the firm-level first and foremost overcomes the lack of precise economic markets in the data. Importantly, the approach to estimate firm market power in output and labor markets does not require a specific underlying market structure, neither with respect to industry and geography. The only restriction we impose in this sense is that firms within the same two-digit industry have the same production parameters across the whole time period.

6.2 Broadband Internet and Firm Market Power

We conduct two main robustness analyses with respect to our main specification, where we investigate the impact of broadband internet on markups and markdowns. First, we aggregate the outcomes to the municipality level. Second, we use calculate markups and markdowns based on a Cobb-Douglas production function. We further provide evidence of parallel trends for markups and markdowns, where we split the sample into an early- and a late-treatment group. We define the early treatment group as those firms that received broadband internet access in either 2000 or 2001, and the late treatment group for those firms with a connection to broadband internet afterwards. Figure D3 shows that the evolution of markups and markdowns was very similar in terms of trends, albeit the levels do differ. This is likely driven by the fact that dense areas were connected first, where the service sector is more dominant.

Figure D4 provides the results for markups and markdowns. It provides evidence that markups are also increasing at the municipality-level. The pattern is very similar to our benchmark specification, where markups are not rising immediately, but do so slowly over time after the introduction of broadband internet. The magnitude of the effect after five years of treatment is also very close to our benchmark analysis, namely by two percentage points. The left panel shows the results for markdowns: While we observe the same trend as in our benchmark analysis, i.e. a decline in markdowns after a municipality obtains access to broadband internet, the impact is estimated with noise. In terms of magnitude, it is lower than in our benchmark analysis.

Figure D5 shows how markups and markdowns evolve across all three measures, i.e. Cobb-Douglas with OLS and GMM, and the translog baseline specification. We denote the Cobb-Douglas GMM specification by "DLW" - based on De Loecker and Warzynski (2012). For markups, the trend is the same, the key difference lies in the first years after obtaining broadband internet access: Based on the Cobb-Douglas production function, markups are declining in the first two years after treatment, whereas they stay close to zero in our benchmark specification based on a translog production function. The decline in markups in the beginning could be simply due to stronger investment in information and communication technology that allows firms to build up the appropriate infrastructure to profit from broadband internet. However, after four and five years, the point estimates about the increase in markups are quite similar, albeit the confidence intervals for both measures are substantially wider for markups based on a Cobb-Douglas production function.

The right panel shows the decline in markdowns for all measures. However, the initial response of markdowns is also different when based on the Cobb-Douglas production function. The trend thereafter is the same as our baseline results, namely a decline in markdowns. But the point estimates are somewhat smaller than in our benchmark analysis, and in the case of the "DLW" specification, i.e. the Cobb-Douglas production function with estimated production parameters based on GMM, the impact is estimated with noise.

There are two key explanations for this (initial) deviation from our baseline results. First, the production function parameters based on a Cobb-Douglas production function are equivalent within (two-digit) sectors, which implies that all variation is coming from the expenditure shares on materials and labor, respectively. This implicitly negates firm heterogeneity with respect to output elasticities within two-digit sectors. The second explanation is that the Cobb-Douglas production function is not a good approximation for the production process. Previous work using the Cobb-Douglas production function as a robustness analysis have primarily worked with data on the manufacturing sector, e.g. De Loecker and Warzynski (2012); Yeh et al. (2022). However, Gechert et al. (2022) state that "empirical literature emphatically rejects the Cobb-Douglas specification". This might be more true for the service sector and construction than the traditional industries of manufacturing.

7 Conclusion

We investigate the impact of the roll-out of broadband internet on market power in mainland France. The access to fast internet can be interpreted as a decline in information frictions for everyone in the economy. We exploit the staggered diffusion of the broadband internet using a difference-in-differences approach with staggered adoption in a multi-period setting and where covariates are explicitly incorporated. We use this approach because the diffusion of broadband internet was primarily driven by local population density. It allows us to causally determine the impact of broadband internet on markups, i.e. market power in output markets, and markdowns, i.e. market power in labor markets.

In order to measure firm market power on output and labor markets, we make use of firm balance sheet data and augment it with matched employer-employee data to obtain full-time equivalent employment. We exploit an extension of the proxy variable literature, where the ratios between output elasticities and expenditure shares are used to determine both markups and markdowns at the firm level. We estimate translog production functions, and based on the parameters we are able to construct output elasticities for materials and labor. We discuss various drawbacks of this approach, but we believe that the drawbacks outweigh drawbacks relating to concentration indices, in particular with respect to the theoretical underpinnings between concentration indices and competition.

We show that markups, i.e. the firm market power on output markets, increases when the municipality in which the firm is located receives access to broadband internet. The increase is indicative of stronger benefits for firms compared to consumers in terms of information frictions, as the theoretical impact is a priori ambiguous. When investigating various mechanisms, we find that the mechanisms related to globalization are particularly important, which holds for both cheaper inputs as well as export. On the other hand, (domestic) outsourcing and advertising play a reduced role. Further, we find that productive and large firms are increasing their markups after obtaining access to broadband internet, which is in line with evidence that "superstar" firms are driving increasing markups.

The impact of broadband internet on markdowns is also theoretically ambiguous, but we can show that markdowns decline when the municipality in which the firm is located receives access to broadband internet. This effect materializes quickly, and is driven by industries where worker representation is stronger. At the same time, labor market tightness and minimum wages do not play an important role. We find evidence that broadband internet increases helps low-skill workers to earn higher wages than high-skilled workers. This is particularly driven by workers that change their employer. However, we also find that markdowns of low-skill workers in a subsample of firms, where large firms are overrepresented, are increasing compared to high-skill workers. This could be driven by low-skill workers switching to larger firms, where they earn higher wages in absolute, but are paid below their marginal revenue product of labor.

Finally, we discuss welfare implications of broadband internet. In a static model of monopoly profits, the decline in marginal costs and the shift of the demand curve imply higher consumer surplus, producer surplus and deadweight loss. However, in dynamic settings the welfare implications of rising markups are ambiguous due to various channels: the rise in markups can reduce welfare due to misallocation, distributional effects and the direction of technology, but welfare can also increase due to increased product variety. At the same time, the reduction in labor market power is unambiguously positive. These different channels make it difficult to judge the welfare implications of broadband internet.

The internet and access to information and communication technology are considered some of the culprits of an increase in firm market power. We show that it is important to distinguish between market power on output and labor markets. Future research should focus on determining the welfare implications of broadband internet. Futher, linking the impact of market power in both output and labor markets to labor market outcomes is an important avenue for future research.

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Appendix A - Deriving Firm-Level Markups and Markdowns

A firm j produces output in period t with the following production technology:

$$Q_{jt} = Q_{jt}(X^1_{jt}, ..., X^V_{jt}, K_{jt}, \omega_{jt}), \tag{12}$$

indicating that the firm relies on flexible inputs denoted by X^v_{jt} and capital (K_{jt}), which is determined in the previous period, in order to produce output. ω_{jt} denotes firm productivity. In order to derive markups and markdowns, we impose that $Q_{jt}(\cdot)$ is continuous and twice differentiable with respect to its arguments.
Firms are cost-minimizing, and the associated Lagrangian function takes on the following form:

$$\mathcal{L} = \sum_{v=1}^{V} P^v_{jt} X^v_{jt} + r_{jt} K_{jt} + \lambda_{jt}(Q_{jt} - Q_{jt}(\cdot)), \tag{13}$$

where P^v_{jt} denotes the price of the flexible input X^v_{jt} and λ_{jt} denotes the marginal cost of production at a given level of output.
In order to compute markups and markdowns, the firm has monopsony power for one flexible input (labor), whereas the market for the second flexible input (material) is characterized by perfect competition. This difference affects the derivation of the Lagrangian function associated with flexible inputs as $\frac{\partial P^v_{jt}}{\partial X^v_{jt}}$ depending on the underlying market structure, i.e. whether the firm possesses buyer power in one market or whether the market is characterized by perfect competition. Specifically, in a competitive market, this derivative is equal to zero, whereas with buyer power it is nonzero.
The first-order conditions of the Lagrangian function with respect to labor and materials, indicated by L and M in the superscripts, respectively, take on the following form:

$$\frac{\partial \mathcal{L}_{jt}}{\partial X^L_{jt}} = P^L_{jt} + \frac{\partial P^L_{jt}}{\partial X^L_{jt}} - \lambda_{jt} \frac{\partial Q_{jt}(\cdot)}{\partial X^L_{jt}} = 0 \tag{14a}$$

$$\frac{\partial \mathcal{L}_{jt}}{\partial X^M_{jt}} = P^M_{jt} - \lambda_{jt} \frac{\partial Q_{jt}(\cdot)}{\partial X^M_{jt}} = 0. \tag{14b}$$

Rearranging the previous equations and multiplying by the ratio of respective input factor (X^v_{jt}) over output (Q_{jt}) yields:

$$\frac{\partial Q_{jt}(\cdot)}{\partial X^L_{jt}} \frac{X^L_{jt}}{Q_{jt}} = \frac{1}{\lambda_{jt}} \frac{P^L_{jt} X^L_{jt}}{Q_{jt}} \Big(1 + \frac{\partial P^L_{jt}}{\partial X^L_{jt}} \frac{X^L_{jt}}{P^L_{jt}}\Big), \tag{15a}$$

$$\frac{\partial Q_{jt}(\cdot)}{\partial X^M_{jt}} \frac{X^M_{jt}}{Q_{jt}} = \frac{1}{\lambda_{jt}} \frac{P^M_{jt} X^M_{jt}}{Q_{jt}}, \tag{15b}$$

which can simplify using various definitions. First, notice that the left-hand side of equations (15a) and (15b) is equal to the output elasticity with respect to labor and materials, respectively, denoted by θ^L_{jt} and θ^M_{jt}. Second, we can exploit the definition of markups, namely price over marginal cost. Specifically, we define the markup as $\mu_{jt} \equiv \frac{P_{jt}}{\lambda_{jt}}$. Third, with the definition of markups, the second fraction in both equations on the right-hand side turns into $\frac{P^v_{jt} X^v_{jt}}{P_{jt} Q_{jt}}$, which represents the expenditure share for all variable inputs. As is common in the proxy variable

literature, we use α^{v}_{jt} to denote the expenditure share. And fourth, the extra term in equation (15a) relates to the upward-sloping labor supply elasticity. This extra term indicates that the presence of monopsony power generates a wedge between the marginal revenue product of labor and the equilibrium wage, which we denote by υ^{L}_{jt}.
Simplifying equation (15a), we can show that the ratio of the output elasticity with respect to labor relative to the expenditure share encompasses both product market power and labor market power. Specifically, we obtain equation 1. And using the same simplifications, with equation (15b) we can show that markups are measured by the ratio of the elasticity with respect to materials and their expenditure share. This result is shown in equation 2.

Appendix B - Estimation of Firm Market Power

Table B1: Overview Sectors for Market Power Estimation

	(1)	(2)	(3)
Nace Rev. 2	Sector Name	# Obs.	# Firms
8	Other mining and quarrying	10,528	1,261
10	Manufacture of food products	369,296	53,429
11	Manufacture of beverages	5,745	745
13	Manufacture of textiles	22,662	2,965
14	Manufacture of wearing apparel	30,410	4,736
15	Manufacture of leather and related products	9,299	1,300
16	Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	43,146	5,760
17	Manufacture of paper and paper products	11,213	1,326
18	Printing and reproduction of recorded media	75,196	9,649
20	Manufacture of chemicals and chemical products	16,155	2,028
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	2,871	374
22	Manufacture of rubber and plastic products	34,569	4,211
23	Manufacture of other non-metallic mineral products	37,838	4,866
24	Manufacture of basic metals	7,567	918
25	Manufacture of fabricated metal products, except machinery and equipment	162,529	19,486
26	Manufacture of computer, electronic and optical products	25,769	3,334
27	Manufacture of electrical equipment	17,743	2,272
28	Manufacture of machinery and equipment n.e.c.	50,677	6,620
29	Manufacture of motor vehicles, trailers and semi-trailers	13,441	1,644
30	Manufacture of other transport equipment	2,290	301
31	Manufacture of furniture	53,771	7,239
32	Other manufacturing	64,590	8,675
33	Repair and installation of machinery and equipment	67,398	8,899
35	Electricity, gas, steam and air conditioning supply	1,108	159
37	Sewerage	1,705	255
38	Waste collection, treatment and disposal activities; materials recovery	10,414	1,498

Continued on next page

Table B1: Overview Sectors for Market Power Estimation (Continued)

41	Construction of buildings	63,575	9,663
42	Civil engineering	15,458	2,042
43	Specialized construction activities	1288671	181,581
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	187,685	27,090
46	Wholesale trade, except of motor vehicles and motorcycles	234,217	35,168
47	Retail trade, except of motor vehicles and motorcycles	523,756	81,863
49	Land transport and transport via pipelines	99,007	13,472
52	Warehousing and support activities for transportation	8,500	1,319
55	Accommodation	138,301	19,781
56	Food and beverage service activities	361,047	61,193
58	Publishing activities	15,806	2,352
59	Motion picture, video and television program production, sound recording and music publishing activities	11,150	1,856
61	Telecommunications	1,277	239
62	Computer programming, consultancy and related activities	8,148	1,642
63	Information service activities	5,598	868
68	Real estate activities	21,749	3,732
69	Legal and accounting activities	15,145	2,489
70	Activities of head offices; management consultancy activitites	13,319	2,497
71	Architectural and engineering activities; technical testing and analysis	54,261	8,703
72	Scientific research and development	3,059	490
73	Advertising and market research	24,246	3,785
74	Other professional, scientific and technical activities	28,392	4,134
75	Veterinary activities	29,473	4,348
77	Rental and leasing activities	12,469	1,981
78	Employment activities	1,015	192
79	Travel agency, tour operator reservation service and related activities	2,272	380
80	Security and investigation activities	2,546	458
81	Services to buildings and landscape activities	52,983	7,960
82	Office administrative, office support and other business support activities	21,058	3,390

Notes: The table provides an overview over the two-digit sectors included in our sample based on the NACE Rev. 2 classificaiton. The number of observations (firm-year cells) and the number of firms relate to the sample which we use to estimate markups and markdowns.

Table B2: Coefficients from GMM Estimation of Market Power

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NACE	β_l	β_{ll}	β_m	β_{mm}	β_k	β_{kk}	β_{lm}	β_{lk}	β_{mk}
8	.88383	.07916	.13191	.0558	-.01848	.04412	-.08994	-.03536	-.04082
10	.68109	.09266	-.01724	.08052	.04032	.02822	-.09813	-.02381	-.0367
11	.90592	.08308	.01638	.06865	.01991	.03365	-.07774	-.05541	-.03484
13	.70884	.08505	.04393	.0738	.11969	.01774	-.09834	-.02692	-.02865
14	.63797	.06674	.07368	.06525	.12322	.03005	-.06894	-.03848	-.02931
15	.69992	.08147	-.0274	.07835	.15882	.02261	-.09755	-.03044	-.0257
16	.78328	.10366	.06712	.07987	.05098	.02883	-.11843	-.02808	-.04047
17	.82552	.07849	-.02695	.07002	.06291	.03013	-.10438	-.04239	-.02459
18	.86362	.1195	-.02777	.08187	.07121	.02058	-.14258	-.03403	-.01728
20	.83479	.0867	-.00748	.07315	.08714	.02502	-.10616	-.0261	-.03559
21	1.13617	.13256	.04074	.06559	.0045	.01272	-.17589	-.05411	.01601
22	.7882	.09303	.01173	.07805	.12189	.01533	-.12169	-.02094	-.0286
23	.77106	.0996	-.00765	.08258	.07427	.02305	-.12034	-.01823	-.03533
24	.97653	.11142	-.03747	.0781	.02296	.03831	-.13145	-.06494	-.02427
25	.88674	.10993	-.00267	.06265	.05099	.02464	-.11144	-.05261	-.0141
26	.67502	.07533	.09649	.07175	.16245	.02377	-.09091	-.01996	-.0457
27	.77319	.08141	-.07014	.08295	.15688	.01528	-.11694	-.01112	-.03429
28	.82932	.11767	-.03617	.07208	.11264	.02023	-.11233	-.04	-.02678
29	.95865	.1186	-.0699	.08217	.11063	.01584	-.14924	-.03026	-.01961
30	.85631	.10595	.03108	.07612	.05363	.02983	-.11669	-.03649	-.03586
31	.80413	.10874	-.05906	.09659	.15484	.01742	-.13934	-.00792	-.04143
32	.74274	.10766	.0168	.06492	.0764	.0238	-.1027	-.03704	-.02212
33	.78554	.10765	-.01129	.06466	.06571	.02177	-.09962	-.034	-.02178
35	.95445	.0615	.18487	.04584	.11707	.04125	-.07588	-.05715	-.04246
37	1.19334	.15192	-.07387	.05012	-.17522	.05476	-.07063	-.13998	-.00095
38	.85847	.09133	.12578	.04222	.01226	.04031	-.07119	-.06375	-.02559
41	.89791	.11632	-.2427	.10711	.16347	.01521	-.14663	-.00396	-.04212
42	.96951	.1282	-.0519	.07864	.02365	.02864	-.12282	-.04678	-.03464
43	.78373	.10215	-.16983	.09479	.05981	.02654	-.12492	-.00468	-.03745
45	.71128	.11625	-.04211	.04653	-.01223	.02399	-.06332	-.03735	-.00803
46	.80633	.11814	.01397	.04599	.06162	.02027	-.08014	-.0544	-.00827
47	.74148	.11724	.01349	.04885	.05801	.02216	-.05648	-.06195	-.01757
49	.86287	.10555	-.01687	.0561	.01142	.02076	-.09874	-.04394	-.01219

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Table B2: Coefficients from GMM Estimation of Market Power (Continued)

52	.80244	.06792	-.07095	.03874	.04873	.01235	-.06782	-.04124	.01025
55	.67893	.09685	.05782	.03214	-.01711	.02648	-.06066	-.03361	-.01298
56	.60355	.08803	-.10556	.08769	.07257	.0195	-.07898	-.01553	-.03242
58	.91841	.10098	-.08249	.06138	.05409	.02708	-.08036	-.07303	-.0128
59	.87081	.11887	.03148	.0428	.13085	.0101	-.07492	-.04829	-.01898
61	.78983	.09423	.02155	.04495	-.02414	.01589	-.07262	-.02774	.00583
62	.71607	.09426	.03171	.04198	.09626	.01872	-.06882	-.03063	-.01043
63	.90453	.08992	.16966	.03433	-.01544	.06023	-.04735	-.09778	-.0385
68	.81835	.09404	-.06413	.06698	-.05213	.02968	-.09277	-.03504	-.01838
69	.65498	.11616	.06867	.03259	.0717	.01594	-.07791	-.03883	-.00822
70	.68899	.09348	.01194	.04752	.07505	.02483	-.0798	-.0244	-.01846
71	.67839	.10996	-.06151	.0571	.08943	.00741	-.09319	-.01935	-.00524
72	.70229	.10701	.17077	.0451	.2421	.00207	-.07397	-.03318	-.03222
73	.67822	.09947	-.0159	.05772	.04059	.0334	-.07689	-.02093	-.03208
74	.76955	.11323	.05698	.05604	.00856	.03183	-.07253	-.04758	-.0348
75	.90896	.09197	-.23607	.10091	.02707	.01012	-.15367	.00366	-.01615
77	1.06342	.0902	-.00251	.03751	-.28266	.06091	-.06747	-.10374	-.00218
78	.47292	.05535	-.07599	.02389	.31063	.00915	.01027	-.02029	-.00777
79	.79026	.15816	-.13314	.06285	.10186	.00905	-.1107	-.04399	-.00113
80	.69958	.05562	.11947	.02137	-.01741	.04472	-.04796	-.04853	-.01138
81	.5755	.07333	.06578	.04128	-.00955	.03314	-.05811	-.03775	-.01371
82	.67665	.08138	-.03342	.05239	.09652	.01579	-.07152	-.02631	-.01404

Notes: The table provides an overview over the vector of GMM coefficients for the output elasticities. As we estimate the output elasticity by 2-digit NACE sector, we present the results by sector. The description of the variables is equivalent to that in equation 4, i.e. single subscripts indicate constitutive terms and double subscripts indicate squared terms. When two different letters are included in the subscript, this indicates an interaction. Finally, l stands for labor, m for materials and k for capital.

Table B3: Difference in GMM Cofficients across Time Periods

NACE	(1) $\Delta\beta_l$	(2) $\Delta\beta_{ll}$	(3) $\Delta\beta_m$	(4) $\Delta\beta_{mm}$	(5) $\Delta\beta_k$	(6) $\Delta\beta_{kk}$	(7) $\Delta\beta_{lm}$	(8) $\Delta\beta_{lk}$	(9) $\Delta\beta_{mk}$
8	.12096	-.04397	-.04055	-.00558	.11269	-.01631	.00507	.01224	.01144
10	-.03409	-.01274	.01361	-.00181	.01637	-.00019	.01437	-.003	-.00115
11	-.29515	-.05812	.09685	.00048	.15872	-.0025	.02232	.04232	-.02211
13	-.0618	-.00769	.02365	.00385	.0125	-.00045	.00229	.01125	-.00987
14	-.05012	-.00177	.02302	.00287	.01909	.00044	-.00533	.01534	-.00339
15	-.09257	-.0101	-.00955	.00709	.04371	-.00382	.00438	.0158	-.00484
16	-.30226	-.03653	.13062	-.00176	.21252	-.00417	.03202	.04163	-.0205
17	-.08685	-.00778	.04615	-.00567	.03721	.00063	.00585	.01362	-.00514
18	-.05275	-.01086	.04545	-.00321	.03007	-.00189	.01116	.00515	-.00426
20	.01967	.0091	-.03833	.00496	.00454	-.00448	-.01753	.00313	.00969
21	.27732	-.01631	.01876	-.00765	-.21643	.01968	.02692	-.0558	.01259
22	-.05367	-.01627	.05128	-.00385	.05001	.00459	.01179	-.00343	-.00123
23	.0333	-.00268	-.00656	.00043	.00209	.00331	.00719	-.00827	-.00309
24	.1808	.03491	-.15936	-.00168	-.02313	.00115	-.0519	-.00071	.02265
25	-.04248	-.00832	.02204	.00181	.01186	.00309	.00652	.00907	-.00979
26	-.0948	-.02142	.05369	.00276	.03084	-.00539	.0035	.02781	-.0086
27	-.12058	-.01884	.07487	-.00455	.01004	.00171	.02065	.00984	-.00807
28	-.01302	.00166	.03977	-.00052	.01449	.00117	.00373	-.00557	-.00322
29	.01611	-.00161	.0402	.00037	-.02308	.00785	.00386	-.00937	-.0048
30	-.06313	.00038	-.0735	-.00013	.29765	-.04372	-.00901	.05791	.016
31	-.09328	-.02004	.05746	-.00087	.05717	.00257	.0098	.01134	-.01201
32	-.03835	-.00834	.02303	.00035	.01406	-.00404	.00949	.00568	-.00546
33	-.03911	-.00592	.02519	.00265	.05504	-.00117	.00115	.01078	-.00983
35	-.37726	.03286	.15689	.01853	.12009	-.01377	-.02568	.0544	-.03141
37	-.05599	-.03877	.08309	-.01197	-.00468	.0101	.03081	.01305	-.01626
38	-.02692	-.00704	-.01491	.0051	-.01537	.00169	-.01085	.01441	-.00218
41	.00896	-.01092	-.03121	.00471	.03368	-.0012	.00652	-.00056	-.00747
42	-.09106	-.01775	.00594	.00048	.12873	-.00968	.00934	.01605	-.00341
43	-.04287	-.01338	.03673	-.00097	.02983	-.00019	.00998	.00914	-.01141
45	-.00382	-.00358	-.0029	.00067	.01878	-.0036	-.00094	.01591	-.00224
46	-.03209	-.01124	.00462	.0008	.02273	-.00559	-.00099	.00967	-.00068
47	-.03334	-.0037	-.00225	.00345	.00665	-.00133	.00104	.01019	-.00362
49	-.03276	.00436	-.00198	-.0035	-.00905	-.00097	.00405	.00352	.00186

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Table B3: Difference in GMM Cofficients across Time Periods (Continued)

52	.17491	.00674	-.02519	.00301	.00874	.00451	-.01511	-.03446	.00916
55	-.02945	-.00488	.04337	.00672	-.00114	-.00211	.00354	.00948	-.00814
56	-.03261	-.00952	-.00387	.00485	.02508	-.00025	.00558	.00617	-.00804
58	.02324	-.01871	-.05138	.01057	-.07914	.01284	.0026	.00021	-.00668
59	.12201	-.00586	-.07262	.01244	-.04065	-.01936	-.00391	.02242	.0115
61	.05326	.0425	.05625	-.01453	-.11598	.00097	-.02988	-.05338	.04597
62	.13242	-.00767	-.03076	.00444	.00022	.00697	-.01077	-.02025	.00598
63	.00206	-.00334	-.03194	.00049	-.02055	.0079	-.01549	-.00063	.0033
68	.01573	.00727	.034	-.00286	-.00419	.00177	-.00158	-.00154	-.00318
69	.13199	.00218	-.02336	.00783	.00812	.00139	-.01397	.00241	-.00453
70	.02645	.00512	-.00095	-.00114	.03121	.0076	.01201	-.00985	-.00554
71	-.03372	.00259	-.01332	-.00035	.03498	-.00488	.00181	.0052	.00279
72	-.0929	-.02724	.19258	-.02102	-.11467	.01816	.0415	.01464	-.03032
73	-.04522	-.02327	.00308	.00268	-.01881	.00506	.00624	.01553	-.0058
74	-.01172	-.01186	.01185	-.00226	.01331	.00622	.01411	-.00778	-.00613
75	-.20392	-.02387	.16994	-.02418	-.04406	.0008	.04438	.00417	.00459
77	-.02735	-.00468	.04947	.00419	.10414	-.00311	.00556	.00504	-.01574
78	.01773	.00148	.14184	-.06274	-.14212	-.00777	.01746	.01674	.03465
79	-.25495	-.01384	-.10967	.01658	.04552	-.04126	.00072	.09536	.01715
80	.07286	.03905	.0022	.01477	.06577	.01287	.01975	-.05253	-.02596
81	.05781	.00313	-.04205	.0137	-.00062	.00046	-.00887	-.00367	-.00133
82	.04028	.00169	.00072	-.00452	-.03668	.00615	.00397	-.01245	.00377

Notes: The table provides an overview over the differences in the vector of GMM coefficients for the output elasticities across two time periods. Specifically, it shows the difference between the second period (2002-2007) and the first period (1996-2001). As we estimate the output elasticity by 2-digit NACE sector, we present the results by sector. The description of the variables is equivalent to that in equation 4, i.e. single subscripts indicate constitutive terms and double subscripts indicate squared terms. When two different letters are included in the subscript, this indicates an interaction. Finally, l stands for labor, m for materials and k for capital.

Table B4: Coefficients from GMM Estimation of Market Power with Two Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
NACE	β_u	β_{uu}	β_s	β_{ss}	β_m	β_{mm}	β_k	β_{kk}	β_{um}	β_{uk}	β_{sm}	β_{sk}	β_{us}	β_{mk}
8	.9219	.07689	.19465	.04022	.04972	.06169	-.06848	.0579	-.06049	-.06507	.01932	-.01354	-.05557	-.0531
10	.86695	.08796	.58847	.08693	-.08084	.08032	-.05193	.03514	-.10245	-.0476	-.03862	-.02668	-.01151	-.02867
11	.91011	.05983	.5159	.04946	-.10269	.07522	-.06646	.04063	-.07389	-.05459	-.03676	-.02684	.00777	-.03646
13	.64361	.07539	.49685	.06403	.02399	.07374	.1049	.01613	-.08568	-.02134	-.02945	-.01141	-.05131	-.03211
14	.5037	.05313	.47776	.07359	.03522	.0657	.12326	.03413	-.04399	-.03791	-.03747	-.00186	-.05406	-.04023
15	.65015	.05986	.45086	.07062	-.12387	.07422	.11498	.02305	-.07855	-.03189	-.0359	.00078	-.05599	-.01623
16	.818	.0885	.40159	.04083	-.01738	.07684	-.00822	.03229	-.10526	-.04449	-.03075	-.01972	-.00502	-.03051
17	.75424	.06564	.35625	.03561	-.11043	.07908	.01138	.01862	-.08612	-.02133	-.03843	.00616	-.02858	-.02204
18	.66079	.08222	.57982	.0832	-.12605	.07944	.05156	.01782	-.08947	-.02651	-.06991	-.00256	-.04423	-.01695
20	.64223	.06881	.57212	.07052	-.11787	.07156	.01782	.02776	-.06279	-.03618	-.05307	-.00624	-.03979	-.02959
21	.79689	.07478	.92371	.10694	-.12663	.06373	-.11626	.02725	-.10574	-.05802	-.08882	-.05255	-.00234	.02533
22	.61935	.07732	.43305	.06171	-.07379	.07552	.20101	.01765	-.08835	-.0245	-.04665	-.00474	-.023	-.02704
23	.75144	.08101	.35826	.03663	-.09968	.07904	.07118	.02527	-.095	-.03027	-.04838	.01902	-.04035	-.02837
24	.61242	.06176	.63983	.09088	-.10602	.07357	.0048	.03488	-.06218	-.03942	-.04864	-.00991	-.07573	-.03064
25	.77102	.10021	.49439	.06046	-.07651	.0658	.01807	.02218	-.09764	-.04435	-.03519	-.0154	-.04296	-.01272
26	.49225	.06948	.52743	.08417	-.02442	.07001	.14023	.00719	-.07351	-.01476	-.06412	-.00486	-.03679	-.02112
27	.66856	.06345	.5922	.06381	-.21241	.07591	.09191	.01621	-.07676	-.02957	-.06964	-.00898	-.01507	-.01547
28	.65861	.08206	.62745	.0817	-.13551	.07127	.07557	.01961	-.07851	-.03097	-.06348	-.00798	-.0413	-.0206
29	.7809	.09791	.67039	.05577	-.23526	.08175	.04835	.01533	-.11827	-.01893	-.06198	-.03019	.00785	-.0059

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Table B4: Coefficients from GMM Estimation of Market Power with Two Skills (Continued)

30	.61166	.0781	.48337	.08433	.01999	.0575	.04887	.01621	-.06603	-.03561	-.05666	.02286	-.06846	-.01244
31	.75192	.07997	.4473	.05985	-.15698	.0888	.12648	.01796	-.09817	-.03037	-.05372	-.00501	-.01049	-.03065
32	.69776	.07002	.58505	.0661	-.11576	.07274	.03675	.02409	-.08549	-.03396	-.06653	-.0118	-.00719	-.01866
33	.68605	.09645	.40884	.05301	-.03272	.06222	.05742	.0213	-.0815	-.03363	-.03113	.00042	-.05662	-.02404
38	.59786	.06171	.37241	.06139	.12952	.03464	.06375	.02718	-.05978	-.03016	-.00061	-.03829	-.00318	-.02123
41	.64183	.07692	.89878	.09295	-.27618	.08624	.1932	-.00031	-.08621	-.01087	-.07547	-.01841	-.03598	-.02475
42	.72446	.09998	.68783	.05414	-.08768	.06894	-.00315	.03231	-.07549	-.05302	-.06175	-.01691	-.02673	-.03084
43	.83079	.09065	.39651	.04057	-.14622	.08634	.03782	.02137	-.10538	-.01864	-.03566	-.00409	-.02169	-.03219
45	.7307	.0942	.5397	.08594	-.01895	.03431	-.15043	.03997	-.03913	-.06362	-.00448	-.03556	-.06319	-.00812
46	.58181	.08856	.6406	.10127	-.00683	.03821	.00532	.02019	-.04825	-.04108	-.02151	-.02125	-.09847	-.00684
47	.67122	.08681	.41874	.08152	-.07217	.04419	.01741	.02236	-.03065	-.06343	-.00182	-.01886	-.0656	-.00599
49	.69247	.08846	.37463	.06183	-.04721	.04455	.00443	.01301	-.06931	-.02714	-.01053	.00233	-.07571	-.00695
52	.45628	.08646	.59364	.08734	-.08211	.02878	-.00155	.00652	-.04872	-.02373	-.01647	.01659	-.14367	.01566
55	.77729	.10034	.3281	.03711	.09375	.03178	-.03105	.02307	-.04182	-.05925	-.00134	-.02386	-.01706	-.0113
56	.6927	.09015	.29645	.03701	-.07886	.06509	.00329	.0231	-.06988	-.03743	-.01986	-.01052	-.02056	-.01712
58	.60604	.06931	.54572	.05818	-.10932	.05079	.02318	.02966	-.05173	-.05162	-.01391	-.02838	-.07419	-.00817
59	.22233	.03334	.73736	.10837	-.01685	.03699	.13278	.00833	-.03004	.00752	-.03433	-.04308	-.05504	-.01727
62	.34556	.0756	.51256	.09222	.00442	.0359	.12684	.03289	-.01558	-.02184	-.02052	-.03157	-.08923	-.02204
63	.66328	.1149	.54103	.08414	.07402	.04049	.0069	.0413	-.01779	-.09784	-.02822	-.01505	-.09386	-.03483
68	.54174	.0579	.56988	.07209	.03701	.04325	-.12703	.03043	-.05663	-.0189	-.01692	-.01376	-.07728	-.01455
69	.61415	.08542	.49734	.0909	.04988	.02354	-.11124	.04044	-.03455	-.05417	-.01894	-.01644	-.10535	-.0082
70	.48068	.06256	.47858	.08591	-.00502	.03399	-.03172	.02881	-.02694	-.03722	-.01234	-.01081	-.07191	-.01246

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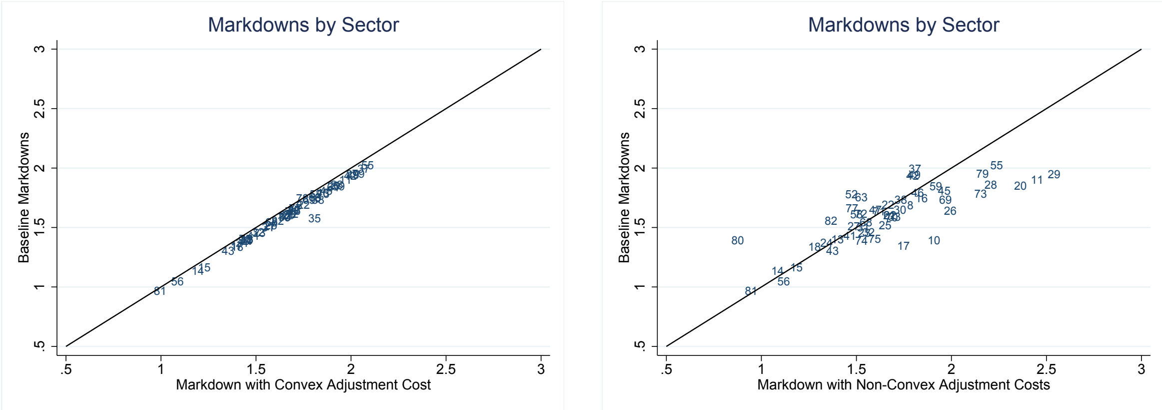
Table B4: Coefficients from GMM Estimation of Market Power with Two Skills (Continued)

71	.46143	.07304	.40862	.07296	-.0674	.05026	.11509	.00598	-.04937	-.01397	-.03018	.0057	-.07694	-.01277
72	.49454	.10077	.44267	.07042	.01377	.05282	.28682	-.00006	-.04782	-.024	-.03823	-.00946	-.07435	-.0259
73	.48397	.07463	.54107	.07635	-.03371	.04484	-.01313	.037	-.02856	-.0386	-.03815	-.00654	-.07408	-.02635
74	.72996	.08279	.54438	.07255	-.00316	.04646	-.11383	.04031	-.03944	-.06181	-.04751	-.02043	-.03904	-.02344
75	.70488	.06601	.42246	.02797	-.26605	.09808	.10014	.0093	-.11166	.01075	-.06507	.00679	.01581	-.03006
77	.93678	.07555	.50674	.07388	.06856	.02655	-.23195	.05488	-.0402	-.10342	-.00931	-.01232	-.0825	-.01069
79	.63842	.15875	.62843	.08718	-.21357	.05045	-.21067	.02771	-.08984	-.04121	-.0372	-.02838	-.07349	.01957
80	.31027	.03551	.69518	.06107	-.05487	.03086	-.19297	.03037	-.01221	.01598	.00816	-.10457	-.03877	-.01396
81	.5577	.06389	.32706	.04324	.07623	.04718	-.02554	.04161	-.06237	-.03646	-.01965	-.00427	-.04415	-.02372
82	.43322	.04892	.59648	.0971	-.05694	.044	.07239	.0138	-.04673	-.00926	-.03519	-.02228	-.04999	-.00789

Notes: The table provides an overview over the vector of GMM coefficients for the output elasticities where we differentiate labor into two skill groups. As we estimate the output elasticity by 2-digit NACE sector, we present the results by sector. Single subscripts indicate constitutive terms and double subscripts indicate squared terms. When two different letters are included in the subscript, this indicates an interaction. Finally, *u* stands for unskilled labor, *h* for skilled labor, *m* for materials and *k* for capital.

Figure B1: Accounting for Labor Adjustment Cost



(a) Benchmark vs. Convex Adjustment Cost

(b) Benchmark vs. Non-Convex Adjustment Cost

Notes: This figure compares the baseline estimates for markdowns by sector with two measures accounting for labor adjustment cost. The left panel shows the estimates for sector-specific markdowns with convex adjustment costs based on the formula derived in Yeh et al. (2022, Eq. (34)), where we assume the same parameter values as the authors: $\beta = .96$ and $\gamma = .185$, where the latter is based on Hall (2004). The right panel contrasts the baseline estimates with non-convex labor adjustment cost. To obtain these estimates, we re-estimate markdowns at the biennial level, assuming that adjustment cost are important at the annual frequency, and less so at the biennial frequency.

Table B5: Markdown Measures with Adjustment Costs

	(1)	(2)	(3)
Nace Rev. 2	Baseline	Convex Adj. Cost	Non-Convex Adj. Cost
8	1.685516	1.679642	1.736071
10	1.391965	1.386778	1.843448
11	1.901693	1.905421	2.386163
13	1.39962	1.388377	1.336035
14	1.133398	1.128926	1.020178
15	1.163764	1.16306	1.119237
16	1.74794	1.743786	1.778108
17	1.344139	1.334422	1.683558
18	1.338468	1.335959	1.214984
20	1.851628	1.844791	2.29879
21	1.603678	1.60556	1.609498
22	1.690325	1.686234	1.601624
23	1.455852	1.453053	1.476947
24	1.373255	1.362403	1.278069
25	1.518486	1.513773	1.587075
26	1.639997	1.63798	1.9296
27	1.509673	1.506569	1.421606
28	1.860714	1.860951	2.142822
29	1.946078	1.942546	2.475462
30	1.647003	1.634807	1.664564
31	1.503489	1.498768	1.471324
32	1.460119	1.445571	1.499612
33	1.591969	1.588014	1.635808
35	1.578578	1.743541	
37	1.995947	2.002175	1.743661
38	1.73409	1.762128	1.668878
41	1.428276	1.421839	1.400985
42	1.935026	1.931791	1.731416
43	1.30268	1.288463	1.309602
45	1.80812	1.804929	1.898435
46	1.790906	1.78682	1.75765
47	1.649017	1.637785	1.53606
49	1.945737	1.946002	1.740087

Continued on next page

Table B5: Markdown Measures with Adjustment Costs (Continued)

52	1.780079	1.74962	1.410091
55	2.023927	2.022571	2.173206
56	1.046747	1.021887	1.052769
58	1.61237	1.612575	1.435938
59	1.847253	1.869673	1.852931
61	1.8365	1.842587	
62	1.602795	1.58991	1.61225
63	1.752368	1.746414	1.46169
68	1.544534	1.517297	1.485684
69	1.731451	1.714627	1.903942
70	1.587711	1.583951	1.620947
71	1.636344	1.620563	1.555698
72	1.613422	1.626223	1.459332
73	1.784911	1.78964	2.089334
74	1.388757	1.382477	1.462726
75	1.404116	1.379307	1.532009
77	1.66061	1.641644	1.412336
78	1.743973	1.679627	
79	1.951654	1.974006	2.098332
80	1.394146	1.373231	.8107768
81	.9667941	.9306445	.8822188
82	1.557782	1.54985	1.302262

Notes: The table provides an overview of our baseline measures of markdowns and the adjustment for convex and non-convex adjustment costs by NACE 2-digit sector.

Appendix C - Data

C.1 Sample Selection

C.1.1 Data Cleaning in Three Stages

We proceed in three stages in the process to determine our final data set. In the first stage, we clean the FICUS data and merge it with the matched employer-employee data set DADS. We largely follow Marinescu et al. (2021) and Combes et al. (2008) in this cleaning process. We drop observations from French overseas territories and Corsica. Further, we concentrate our analysis on firms in the private sector excluding both agriculture and financial and insurance activities.[28] We also exclude employers categorized as museums, art industry, sports clubs, unions and home production. We drop all observations with zero or negative total wage bills, material inputs, capital, value added or output. Finally, we keep only the longest spell of consecutive periods of a firm, and require to observe at least three consecutive years in our sample.
Before the merge between FICUS and the DADS, we also clean these files in line with previous work. Specifically, we exclude state-sponsored workers, apprentices, interns and workers with remaining occupations in the agricultural sector. We keep part-time employees, otherwise we would substantially underestimate the full-time equivalent employees per firm. We keep workers between the ages of 18 and 67. Lastly, we drop observations with zero or negative hours worked in a given year. After the cleaning procedure of both data sets, we only lose .21% of firms in the FICUS data set compared to its merge with the DADS Salariés. This second step in the first stage allows us to construct full-time equivalent employment for all firms from 1996 onwards. After cleaning the data sets and merging them, we call it the “cleaned and merged” sample.
In the second stage, we restrict our sample in the process of estimating firm-level markups and markdowns. We call this sample the “post-market power estimation” sample The restriction is due to three reasons. First, we lose the year 1996 due to the GMM estimation procedure. Second, we exclude firms with expenditure shares smaller than 2.5% for either labor or materials, though the latter is more important, specifically for firms in the service sector. We exclude these firms because the low expenditure shares, i.e. α^L and α^M, strongly drive up our measures of markdowns and markups.[29] Third, we exclude the top and bottom two percent of outliers of both markups and markdowns by sector. Lastly, due to the GMM estimation, we lose the year 1996 and this sample starts in 1997. These changes result in a loss of 33% of observations, though the single most important driver is the loss of the year 1996.
In the third stage, we construct our final sample after estimating firm level markups and markdowns. This is for three reasons. First, due to dropping outliers and firms with low (corrected) expenditure shares, we observe spells with gaps. For our difference-in-differences approach, we also require to observe consecutive spells, so we again require to observe at least three consecutive periods per firm. Further, we only keep firms in the sample which we observe at least one year before and at least one year after the introduction of broadband internet. Finally, we drop firms that are located in communities with a population smaller than 100 during the 1999 census. These requirements lead to a reduction of 30% compared to the post-market power estimation sample, and a reduction by 55% compared to the cleaned and merged sample.

[28] It is difficult to estimate meaningful production function parameters for financial and insurance activities, thus providing us with either excessive or potentially negative markups and/or markdowns. This is in line with standard procedures of estimating markups, e.g. Weche and Wambach (2021).

[29] The same logic applies to using energy as an input in the discussion of the estimation of markups and markdowns above.

Our final sample stretches from 1997 until 2007. Though FICUS data are available from 1994 onwards, we start two years later because FICUS does not contain full-time equivalent employment. Instead, we recreate full-time equivalent employment with the help of DADS Salariés. However, this data is not available for 1994 nor 1995. We limit ourselves to the time period until 2007 for three reasons. First, we want to exclude any confounding impact from the Great Financial Crisis. Second, the change from FARE to FICUS occurred in 2008, and some measures are not perfectly equivalent across the two data sets.[30] Third, the expansion of broadband internet was essentially finished in 2006, thus we do not gain much more information from extending the time period in our analysis.

C.1.2 Comparison across Sample Selection Stages

In order to understand how representative our final sample is of the French economy, we compare the summary statistics of our different samples.[31] Table C1 in the appendix shows how our sample evolves with our sample restrictions. It shows means and standard deviations, respectively, for various variables, such as output, value added, material inputs, capital, wage bill (all logged), full-time equivalent employment and the shares of manufacturing, construction and service firms, as well as the share of firms in Paris. After the first step, i.e. in our "cleaned & merged" sample, we obtain 4,342,476 firm-year observations shown in columns (1) and (2). We observe that (logged) output is equal to 5.99, full-time equivalent employment is 8.56 with a large standard deviation of 28.03, and that the share of manufacturing firms is equal to .26, of construction it equals .31, and that of services equals .43.

After the second stage, i.e. post-market power estimation, we have 2,882,532 firm-year observations. With respect to the variables used to estimate markups and markdowns, we see an overall increase in both output/value added and the inputs (materials, capital), though average employment declines. This indicates that we tend to lose small firms with respect to overall inputs during the estimation of markups and markdowns. With respect to sectoral composition we observe substantial shifts: the share of manufacturing firms increases by four percentage points (from 26 to 30 percent), and the share of construction firms rises even stronger, namely by eight percentage points (from 31 to 39 percent). On the other hand, the share of service firms drops from 43 to 31 percent, i.e. by 12 percentage points.

After the third and final stage, the aforementioned trends in sectoral composition and size are exacerbated. Output, value added and all inputs - including full-time equivalent employment - continue to rise. For example, average employment is equal to 9.62 in the final sample compared to 8.56 in the cleaned and merged sample and 8.47 in the post-market power estimation sample. Similarly, (log) output is equal to 6.22 in the final sample compared to 5.99 in cleand and merged sample and 6.08 in the post-market power estimation sample. In terms of sectoral shares, the final sample contains less service sector firms than before, and more manufacturing and construction firms. Precisely, service sector firms are making up a share of 27%, and the sample consists of 32% manufacturing firms and 41% of construction firms.

The bias in the sectoral composition is quite strong, that is why we construct weights in order to make our final sample more representative of the French economy in terms of sectoral shares. We do not adjust our weights in terms of the large firm bias as it is quite typical of data cleaning procedures and the literature documents that large firms are the main driver for an increase in

[30]This is primarily true for output in the wholesale and retail trade sector. For manufacturing this change does not seem to have any effect.

[31]Below, we contrast the descriptive statistics of markups and markdowns between the post-market power estimation sample and the final sample.

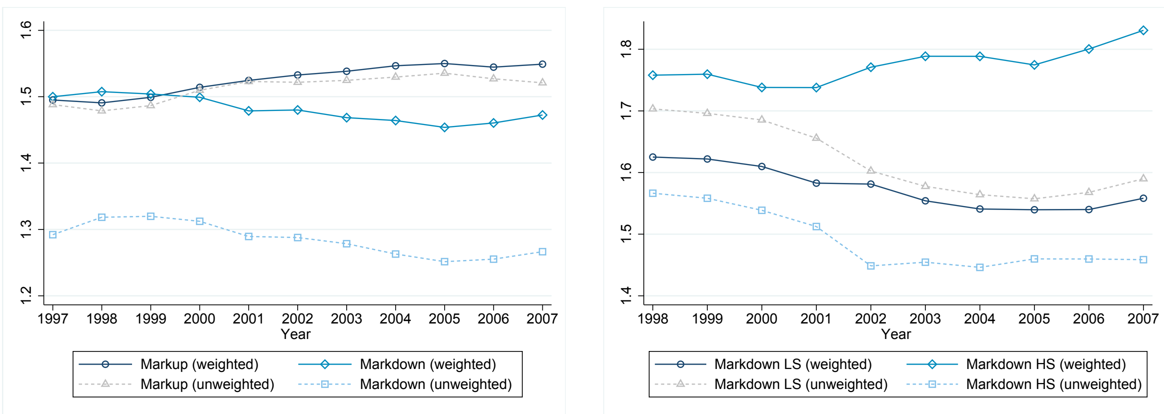
markups (De Loecker and Eeckhout, 2018; Autor et al., 2020). Below in the summary statistics (Table C2), we show the success of our weighting variable for a better representativeness of the sectoral composition.

Table C1: Comparison Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Cleaned & Merged		**Post-MP Estimation**		**Final Sample**	
	Mean		SD		Mean	
Log Output	5.97	1.22	6.16	1.12	6.30	1.12
Log Value Added	5.23	1.18	5.37	1.06	5.51	1.05
Log Materials	3.81	1.95	4.84	1.22	4.99	1.22
Log Capital	4.51	1.47	4.62	1.35	4.79	1.33
Log Wagebill	4.46	1.35	4.66	1.16	4.82	1.15
Employment	8.54	30.07	8.41	20.62	9.46	21.50
Share Firms in Paris	0.17	0.37	0.12	0.33	0.10	0.30
Share Manufacturing	0.26	0.44	0.32	0.47	0.34	0.47
Share Construction	0.31	0.46	0.47	0.50	0.49	0.50
Share Service	0.42	0.49	0.21	0.41	0.17	0.38
Observations	4,234,967		1,923,959		1,328,214	

Notes: The table presents how our sample changes throughout the three stages of sample selection. The first two columns show summary statistics (means and standard deviations) based on cleaning the raw data and the merge with the DADS to obtain firm-level employment. The second two columns present summary statistics after the estimation of markups and markdowns, and the last two columns provide an overview of our sample we use in our difference-in-differences estimation, i.e. our final sample. All samples are unweighted, and the latter two samples focus on the sample where we estimate markups and markdowns based on a translog production function.

Figure C1: Market Power Trends (based on Post-Estimation Sample)



(a) Markups and Markdowns

(b) Markdowns by Skill

Notes: This figure shows the evolution of market power in both product markets and labor markets, both unweighted and weighted. Markups are weighted by sales, and markdowns are weighted by employment. The right panel differentiates markdowns by skill, and contains only markdowns for firms which employ both low- and high-skilled workers. These markdowns are weighted by the share of low- and high-skill employment, respectively.

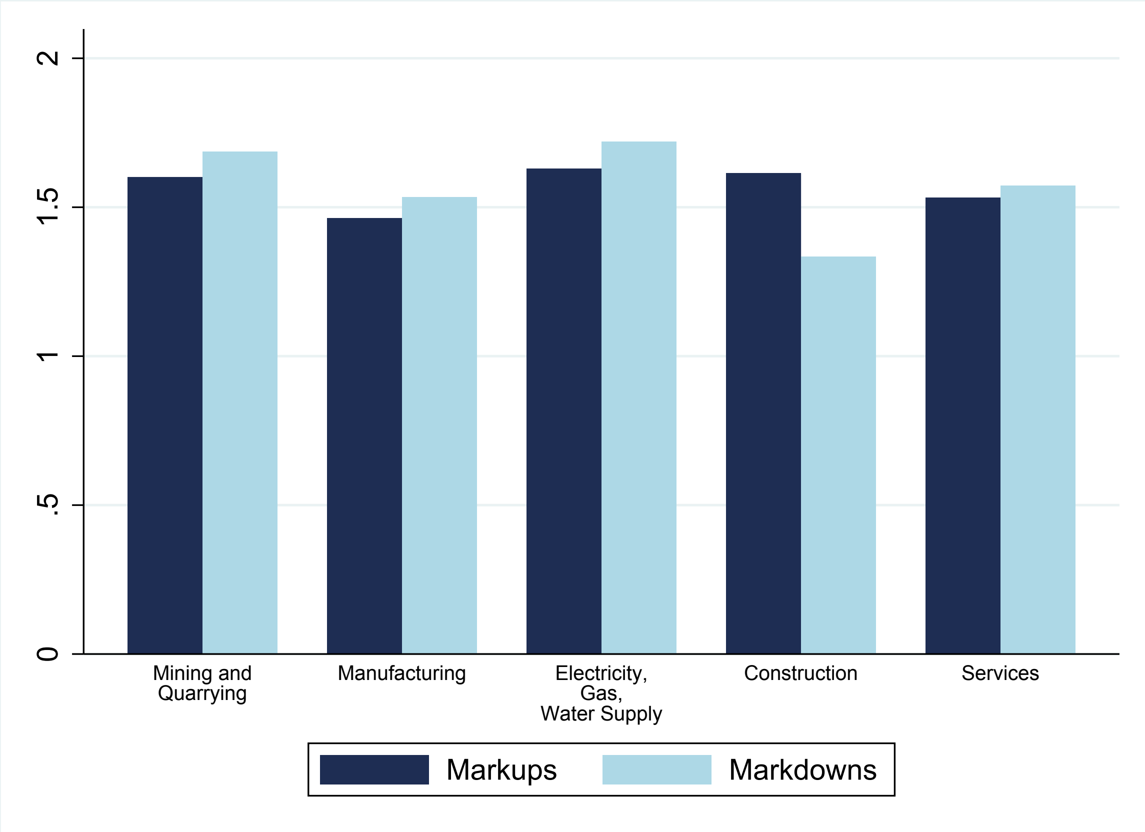
Table C2: Summary Statistics

multicolumn6c*Panel B: Firm Level*

	Obs.	Mean	Std.Dev.	P25	P75
Markup (DLW Translog)	1328214	1.50	0.23	1.35	1.63
Markdown (DLW Translog)	1328214	1.32	0.44	0.99	1.58
Markdown Low-Skill (DLW Translog)	191431	1.69	0.49	1.32	1.98
Markdown High-Skill (DLW Translog)	191431	1.54	0.68	1.02	1.89
Share High-Skill Workers	216851	0.24	0.13	0.14	0.31
Firm Size	1485360	9.98	23.03	2.05	9.46
Share Firms in Paris	1485360	0.11	0.32	0.00	0.00
Share Manufacturing Firms	1485360	0.26	0.44	0.00	1.00
Share Construction Firms	1485360	0.31	0.46	0.00	1.00
Share Service Firms	1485360	0.43	0.49	0.00	1.00
Panel B: Municipality Level					
Markup (DLW Translog)	220817	1.47	0.15	1.37	1.55
Markdown (DLW Translog)	220817	1.36	0.31	1.16	1.53
Markdown Low-Skill (DLW Translog)	68703	1.68	0.40	1.40	1.90
Markdown High-Skill (DLW Translog)	68703	1.51	0.55	1.12	1.77
Share High-Skill Workers	72369	0.23	0.11	0.15	0.28
Firm Size	227025	8.23	12.24	2.76	9.59
# of Firms in City	227025	6.54	17.62	1.00	6.00

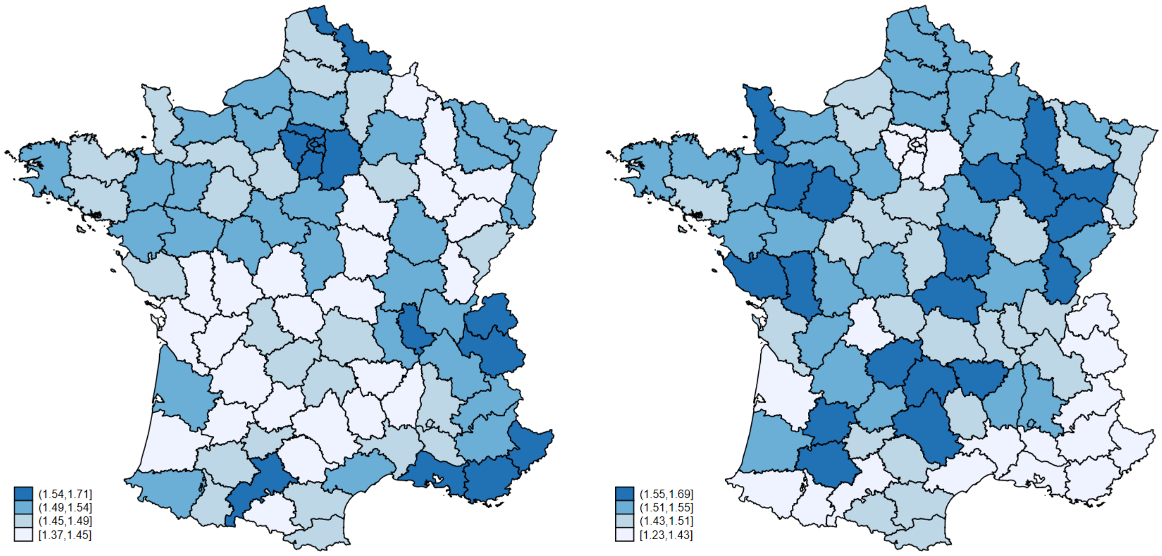
Notes: This table presents the summary statistics fo the main variables used in the analysis. The statistics are computed over the full time period from 1997 until 2007. Observations are weighted such that sectoral composition is the same after cleaning the raw data.

Figure C2: Market Power by Industry (based on Post-Estimation Sample)



Notes: This bar chart shows the average markups and markdowns weighted by sales and employment, respectively, across 1-digit sectors according to NACE Rev. 2. Manufacturing, construction and services make up 99% percent of firms in the sample.

Figure C3: Geographic Distribution of Market Power (based on Post-Estimation Sample)

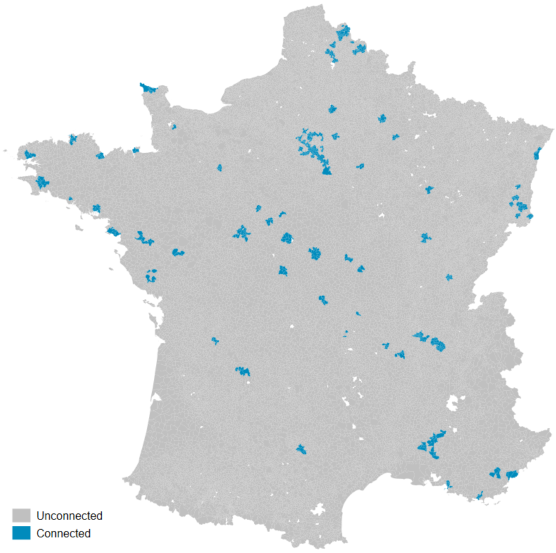


(a) Markups

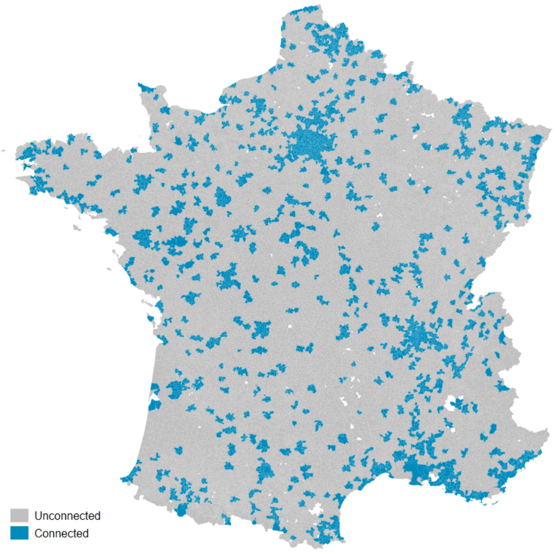
(b) Markdowns

Notes: The maps show the spatial distribution of markups (left) and markdowns (right) in mainland France. The geographic allocation is based on the information on the “département ” in the FICUS data.

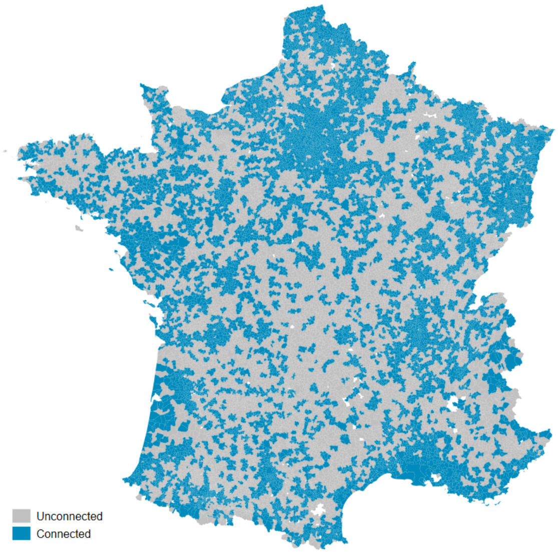
Figure C4: Diffusion of Broadband Internet



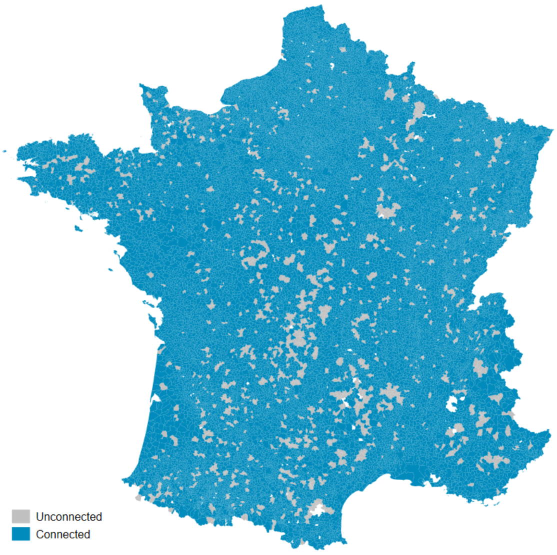
(a) 2000



(b) 2002



(c) 2004

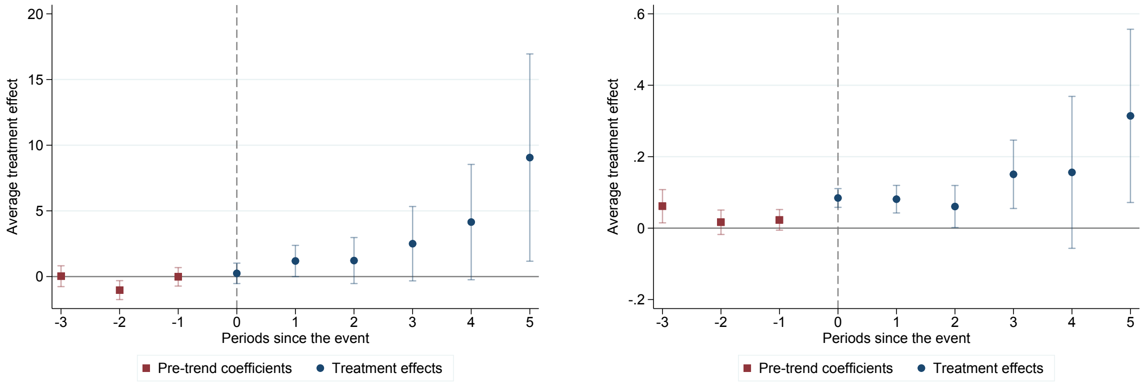


(d) 2006

The maps show the expansion of broadband internet throughout the first years of the early 2000s in France. A "commune" is indicated in blue as connected, once it has a positive, i.e. non-zero, value in the measure of broadband access $\tilde{Z}_{lt}$ defined in equation (11).

Appendix D - Robustness Analysis

Figure D1: Internet Access and Wages

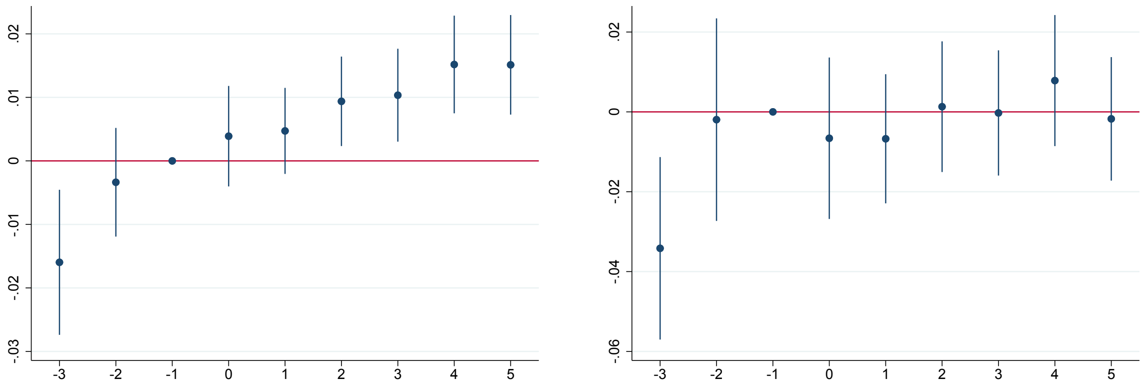


(a) Firm Wage Bill

(b) Employee Hourly Wages

Notes: This figure shows the rise in wages after connection to broadband internet access. The left panel uses the firm wage bill as an outcome variable, while the right panel uses hourly wages on the worker level from the EDP sample.

Figure D2: Changing Employer by Skill (Educational Classification)

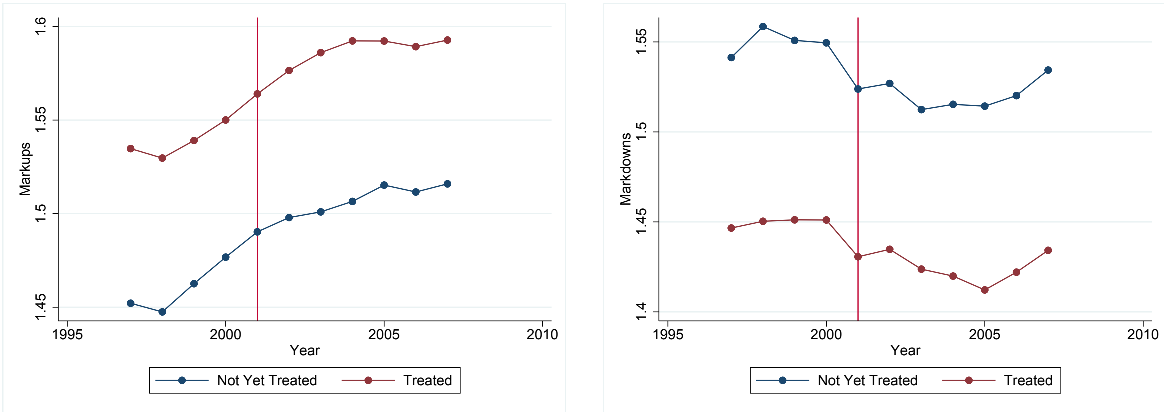


(a) Low-Skill

(b) Educational Classification

Notes: This figure shows the estimation results for a triple difference-in-differences estimation, where we regress wages on the arrival of broadband internet interacted with changing the employer. It is based on data from the EDP, and we keep only workers who changed their employer at most once during the sample period. We run the regression separately by skill skill level based on educational classification.

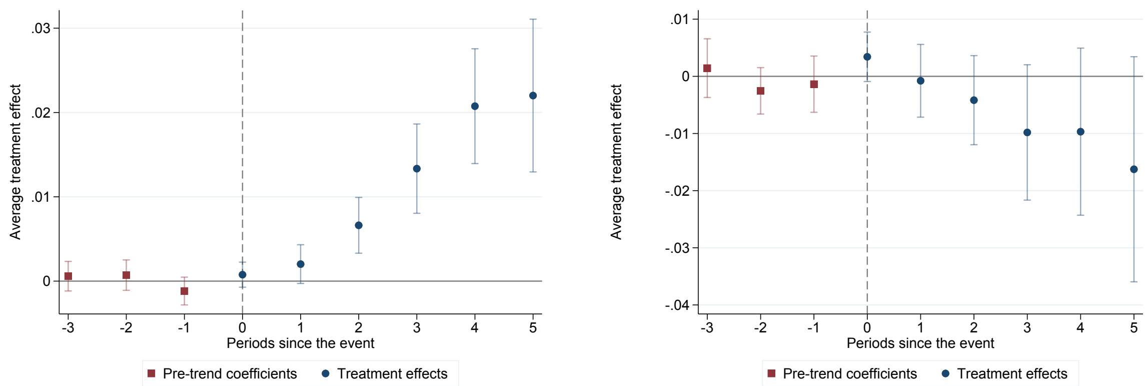
Figure D3: Pre-Trends



(a) Markups (b) Markdowns

Notes: This figure shows the pre-trends for markups and markdowns. However, as all firms and municipalities are treated in our sample, we divide our sample into an early- and a late-treatment group. We define the early-treatment group if the municipality where the firm is located has been connected to broadband internet in 2000 or 2001.

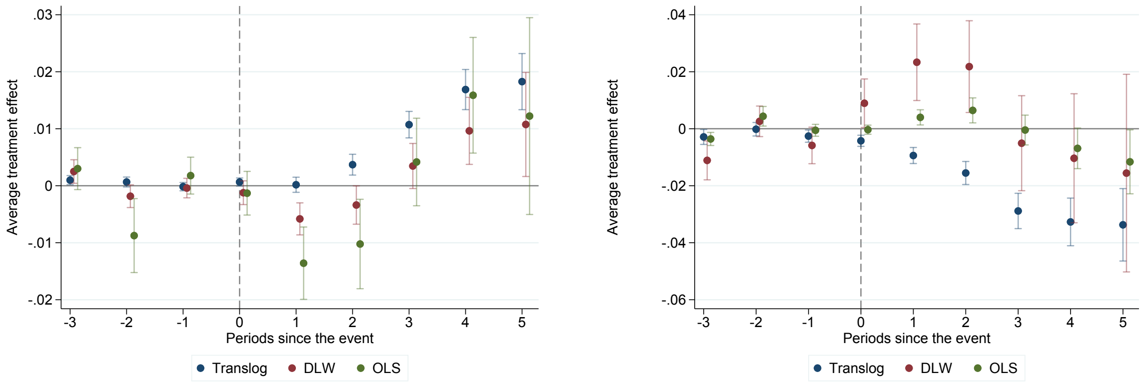
Figure D4: Municipality-Level Regressions



(a) Markups (b) Markdowns

Notes: This figure shows the estimation results of our baseline specification, but aggregated to the municipality level. Instead of firm-fixed effects we use municipality-fixed effects, otherwise the estimation takes on the same form as equation (10). In this specification, we weigh observations by the number of firms located in the municipality.

Figure D5: Translog and Cobb-Douglas Measures

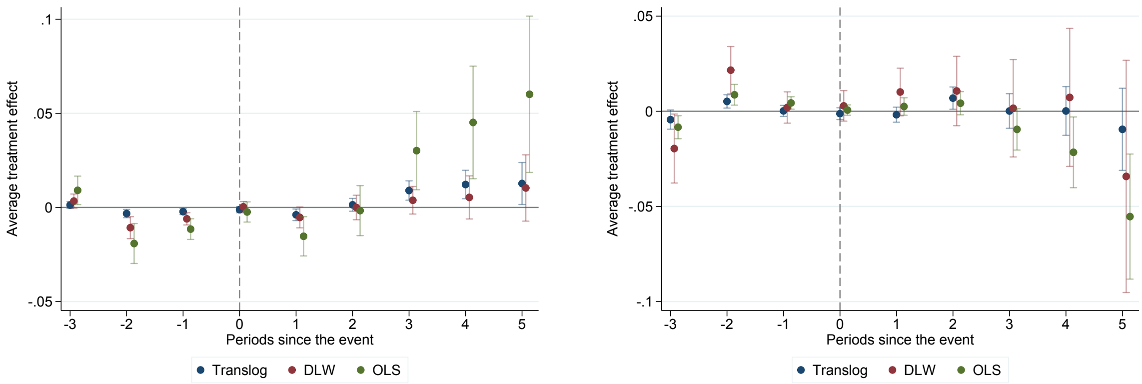


(a) Markups

(b) Markdowns

Notes: This figure shows the estimation results across three measures of markups and markdowns, respectively. Specifically it shows the results for a Cobb-Douglas production function estimated with with OLS and GMM, and the translog baseline specification. We denote the Cobb-Douglas GMM specification by "DLW".

Figure D6: Translog and Cobb-Douglas Measures - Manufacturing

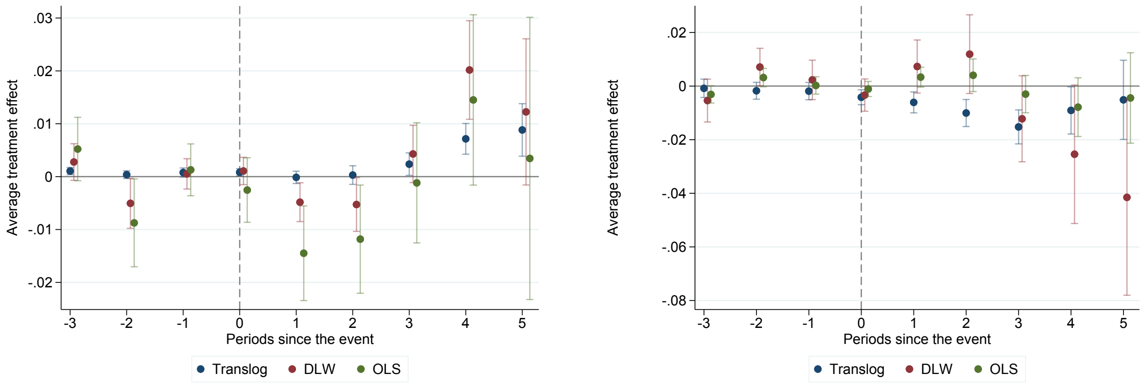


(a) Markups

(b) Markdowns

Notes: This figure shows the estimation results across three measures of markups and markdowns, respectively, for the manufacturing sector. Specifically it shows the results for a Cobb-Douglas production function estimated with with OLS and GMM, and the translog baseline specification. We denote the Cobb-Douglas GMM specification by "DLW".

Figure D7: Translog and Cobb-Douglas Measures - Construction

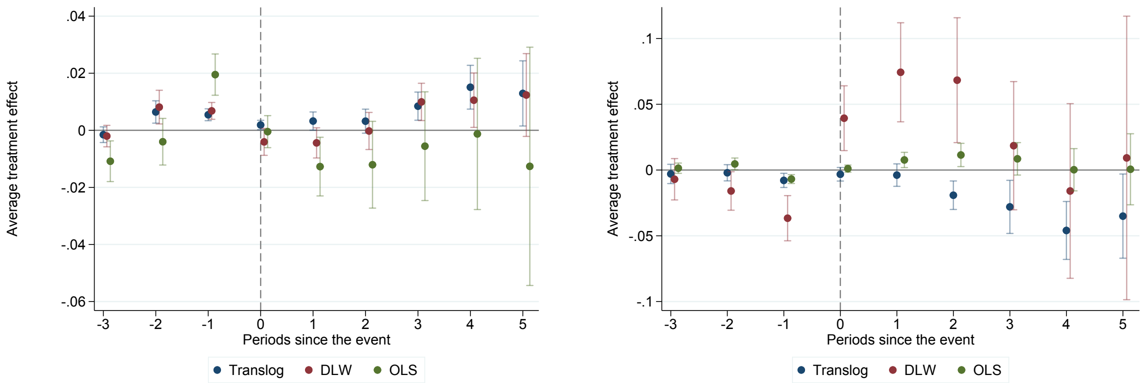


(a) Markups

(b) Markdowns

Notes: This figure shows the estimation results across three measures of markups and markdowns, respectively, for the construction sector. Specifically it shows the results for a Cobb-Douglas production function estimated with with OLS and GMM, and the translog baseline specification. We denote the Cobb-Douglas GMM specification by "DLW".

Figure D8: Translog and Cobb-Douglas Measures - Services



(a) Markups

(b) Markdowns

Notes: This figure shows the estimation results across three measures of markups and markdowns, respectively, for the service sector. Specifically it shows the results for a Cobb-Douglas production function estimated with with OLS and GMM, and the translog baseline specification. We denote the Cobb-Douglas GMM specification by "DLW".