Wage and Employment Effects of Wage Subsidies*

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Abstract

This paper provides new evidence on how wage subsidies affect wages and employment. Using French administrative data, a 2015 nationwide wage subsidy reform, and a shift-share IV design, I leverage variation in reform exposure across local labor markets stemming from differences in the socio-economic composition of the local working-age population. Local labor markets more exposed to an increase in wage subsidies see faster growth in hours worked–driven mainly by rising employment–and slower growth in average hourly wages. The economic incidence is not borne solely by workers, as 31% of the subsidy passes through to wages on average.

JEL classification codes: H22, H23, H24, H31, J22, J31.

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1 Introduction

Direct government transfers to workers in the form of wage subsidies are widely implemented anti-poverty programs. They provide financial support to poor working families together with additional incentives to work. A prime example of their popularity is the Earned Income Tax Credit (EITC) in the United States, which has experienced multiple federal and state expansions since its implementation in 1975. In 2021, it represented approximately $60 billion for 25 million workers. In France, the context of this paper, an average of 5 million workers benefited from a wage subsidy program similar to the EITC in 2020, at a cost estimated to be €10 billion (DREES, 2021).

Despite a large body of literature evaluating the employment effects of these transfers, there is still limited evidence regarding who benefits from them between workers and employers.[1] Indeed, wage subsidies can have unintended effects in the presence of labor market equilibrium effects (Rothstein, 2010). By making work more profitable for workers, the total number of hours worked in the economy increases. This increase in employment decreases the prospective average hourly wage rate for a given labor demand. Ultimately, workers may not fully benefit from wage subsidies as employers are able to capture part of them through reduced real wage growth (Rothstein, 2010; Leigh, 2010; Azmat, 2019; Kroft et al., 2020; Zurla, 2024).

This paper empirically challenges the idea that the economic incidence of wage subsidies falls entirely on workers by moving away from the conventional no wage effect assumption. I present novel causal estimates of the effect of wage subsidies on wage and employment at the local labor market level. To do so, I develop a shift-share IV design that exploits differences in the exposure to a national reform in wage subsidies in France, based on the socio-economic composition of the local working-age population.

Most of the recent microeconomic literature on wage subsidies focuses on labor supply responses by workers, casting aside equilibrium effects on the labor market (e.g., Eissa & Liebman, 1996; Meyer & Rosenbaum, 2001; Grogger, 2003; Hotz & Scholz, 2006; Bollinger et al., 2009; Gelber & Mitchell, 2012; Chetty, Friedman, et al., 2013; Chetty & Saez, 2013; Bastian, 2020; Agostinelli et al., 2021; Whitmore Schanzenbach & Strain, 2021; Kleven, 2024). It is equivalent to the implicit assumption that the hourly wage rate is fixed or that labor demand is completely elastic.

In this context, causal evidence on the extensive margin (the probability of participating in the labor market and to be employed) and intensive margin (the number of hours worked conditional on employment) are estimated by comparing individuals from the same labor market, some experiencing an increase in wage subsidies and others not. While this estimation strategy is effective for evaluating employment effects of wage subsidies, it cannot capture wage effects. Since both treated and control groups participate in the same labor market, any increase in employment in the treated group could reduce the hourly wage rate in the control group. By

[1] See Hoynes (2019) for a recent review.

extension, it is also unhelpful to estimate the overall effect on labor earnings. Taking into account this channel has substantial implications in assessing who really benefits from these policies between employers and workers.

Disentangling the wage and employment channels of wage subsidies in the presence of labor market equilibrium effects is challenging (Imbens, 2014). A suitable research design must allow for responses in both labor supply and labor demand. This paper provides a new perspective on this question by using a novel identification strategy and a unique 2015 wage subsidy reform in France. In France, wage subsidies are set at the national level and are paid directly to workers. Although they depend on individual and household characteristics (such as labor earnings, marital status or the number of children), they do not depend on specific local labor market characteristics. Conditional on having similar characteristics, an individual living in the north of France receives the same amount of wage subsidy as someone living in the south of France. The reform merged two wage subsidy programs, creating shocks that differ along individual and household characteristics. As a result, some local labor markets were more exposed to the reform on average. Intuitively, the identification strategy compares two labor markets facing the same reform, but for which the overall change in wage subsidies received will be different because of initial differences in the distribution of these socio-economic characteristics.

I take advantage of a high-quality dataset on a representative sample of French individuals, combining administrative data matching employer-employee information with income tax returns and social agencies claims.[2] In particular, sampled individuals are followed over time, allowing me to precisely track their labor market outcomes. This unique combination of a national-level reform, high-quality data, and a heterogeneous population makes the French context particularly suitable for studying the wage and employment effects of wage subsidies.

First, I outline a simple conceptual framework to guide the empirical analysis. I start with a competitive labor market model, based on Rothstein (2010), that incorporates equilibrium effects of wage subsidies. This model considers both extensive and intensive labor supply responses, with local labor markets composed of agents with diverse socio-economic characteristics, as used for determining wage subsidies (e.g., household income, marital status, or children). This simple model highlights how a labor market level analysis provides sufficient statistics to assess the wage and employment effects of wage subsidies. It shows that an increase in labor supply at the local labor market level will partly reduce hourly wage rates if labor demand is less than perfectly elastic.

Next, I develop a quasi-experimental research design to identify the wage and employment effects of wage subsidies. A key contribution of this study is to show that causal estimates for both effects can be recovered via local labor market level regressions using a shift-share instrumental variable design. This identification stems from two factors. First, the wage subsidy

[2] This dataset, called the *Echantillon Démographique Permanent*, has not been extensively used in the public finance literature. It provides a unique and exceptional combination of administrative datasets, somewhat akin to the data available in Scandinavian countries, that allow for a precise description of individuals' and households' income dynamics (Aghion et al., 2023).

eligibility requirements and schedule are set at the national level. It depends mainly on individual characteristics (such as labor earnings) and household characteristics (such as income, marital status, and number of dependents). Importantly, it does not depend on which local labor market people are in. For example, for a given set of socio-economic characteristics, wage subsidies are not higher in depressed areas than in prosperous ones. Second, individual and household characteristics are heterogeneously distributed across local labor markets. The combination of these two features makes some local labor markets more exposed than others to a change in wage subsidies decided at the national level. I construct two relevant exposure measures for the analysis: the hour-weighted change in the marginal tax rate and the hour-weighted change in the average tax rate at the local labor market level.

The validity of my research design relies on the quasi-random assignment of shocks (Borusyak et al., 2022). This approach assumes that changes in wage subsidies were not strategically set based on changes in local labor market trends. This assumption naturally holds in the French context because the wage subsidy schedule is set at the national level and is not directly indexed to local labor market characteristics. However, reverse causality between wage subsidies and labor earnings is a potential threat to identification. To address this, I build on the simulated instruments literature and calculate tax shocks under the assumption of no behavioral responses to the reform (e.g., Auten & Carroll, 1999; Moffitt & Wilhelm, 2000; Gruber & Saez, 2002; Kopczuk, 2005; Weber, 2014). To further validate my research design and demonstrate that changes in wage subsidies are not correlated with other unobservable local labor market features affecting wages and employment, I conduct a series of falsification tests.

Then, I evaluate the 2015 French wage subsidy reform's effects using this quasi-experimental research design. I find significant wage and employment responses with respect to the average tax rate but no significant response with respect to the marginal tax rate. Specifically, a 10% decrease in the average tax rate increases hours worked by 2.70% and decreases the hourly wage rate by 3.09% relative to a scenario with no wage subsidy change. Overall, there is no significant effect on pre-tax labor earnings growth at the local labor market level, as wage and employment effects offset each other. The wage effect implies an average pass-through of wage subsidies to wages equal to 31%.

Finally, I examine the mechanisms through which wage subsidies affect wages and employment at the microeconomic level. Wage subsidies have both a direct effect, as they encourage individuals to participate more in the labor market and work additional hours, and an indirect effect, where an increased labor supply leads to lower wages due to market adjustments. The direct effect is the intended goal of wage subsidies: boosting employment by making work more attractive. The indirect effect happens when the increased number of workers puts downward pressure on wages, which could subsequently reduce labor supply. I develop an empirical strategy that isolates the micro-level employment and labor supply responses. It shows that direct effect operates mainly at the extensive margin. A 10% decrease in the average tax rate raises the employment rate by 1.59% and hours worked by 3.14%. In contrast, wage subsidies have no direct impact on wages, indicating that wages are determined only through market-level equilibrium forces.

Related literature. This paper builds on and contributes to several strands of literature. First, there is a vast body of literature on the effects of wage subsidies on the labor market. A very important microeconomic literature has focused its attention on the effect of these programs on the labor supply of individuals (surveyed by Hotz (2003), Eissa and Hoynes (2006), Meyer (2010), Nichols and Rothstein (2015), Hoynes and Rothstein (2016), Brewer and Hoynes (2019), Hoynes (2019)).

A large literature finds significant extensive margin responses to wage subsidies, particularly the EITC (e.g., Eissa & Liebman, 1996; Meyer & Rosenbaum, 2001; Grogger, 2003; Hotz & Scholz, 2006; Gelber & Mitchell, 2012; Bastian, 2020; Whitmore Schanzenbach & Strain, 2021). However, Kleven (2024) argues that most EITC extensions had no effects on employment or that any observed effects are likely due to changes in other welfare programs and macroeconomic conditions. Evidence of intensive margin responses is more scarce. In particular, Chetty, Friedman, et al. (2013) find large and significant responses to kinks in the EITC schedule. However, Bollinger et al. (2009) and Chetty and Saez (2013) find more nuanced and minimal responses at the intensive margin. Overall, this literature considers the equilibrium effects to be negligible, implicitly assuming exogenous wage rates.

This paper departs from this assumption by allowing for equilibrium effects and empirically investigating both wage and employment channels. Although some studies have moved away from this canonical setting (Rothstein, 2010; Leigh, 2010; Azmat, 2019; Kroft et al., 2020; Zurla, 2024), we still have limited evidence because of the difficulty in identifying such effects using credible research designs and the unavailability of administrative and/or panel data. The closest empirical study to mine is by Leigh (2010), who finds that an increase in the EITC reduces the hourly wage rate for both high school dropouts and high school graduates. However, his estimates imply an average pass-through of wage subsidies to wages of 500%, which is inconsistent with standard incidence predictions. Relative to this literature, the key contribution of this paper is the development of a quasi-experimental research design that can credibly estimate wage and employment effects separately at the labor market level.[3] To do so, I combine recent advances in Bartik/shift-share IV design (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), panel data from high-quality French administrative sources, and a large reform in wage subsidies that occurred in 2015 in France.

Second, this paper contributes to the scarce literature on the incidence of wage subsidies.[4]

[3] Kroft et al. (2020) develop an optimal taxation model that includes wage effects in the presence of involuntary unemployment. Using an empirical strategy that exploits variation in tax liabilities from EITC reforms between 1994 and 2010, they estimate both micro and macro (at the U.S. state level) participation and employment elasticities. However, they do not directly estimate the wage effect of wage subsidies.

[4] A substantial portion of the incidence literature addresses labor taxes in the form of payroll taxes (see Benzarti (2024) for a review). Benzarti (2024) also highlights the scarcity of work on income taxes–including the Earned Income Tax Credit–due to challenges in identifying robust research designs. This paper aims to help fill that gap.

By disentangling the wage effect from the employment effect, I estimate the share of the subsidy that goes to employers versus workers. Rothstein (2010) investigates the incidence of the EITC using a competitive partial equilibrium model for the labor market and calibrations across a range of plausible values for the labor supply and demand elasticities. Focusing on the labor market for women, he finds an average pass-through of 30% for low-skilled mothers. Zurla (2024) estimates a pass-through rate of 30% at the firm-level, within the context of an Italian EITC program administered by firms. Azmat (2019) shows, also in the context of an employer-administered tax credit in the UK, that firms cut the wage of claimants by 7% relative to non-claiments, suggesting a negative spillover between the two groups. The French EITC is not administered by firm and is similar in practice to the US EITC. In this context, I show that employers are able to capture a sizeable part of wage subsidies–up to 31% on average–through reduced wage growth.

Finally, this paper contributes to the growing literature estimating the macroeconomic effects of taxes and transfers, including wages subsidies (Froemel & Gottlieb, 2021; Ortigueira & Siassi, 2022; Ferriere et al., 2023). I show how my estimation strategy is compatible with a model aggregating individual and household responses at the relevant market level. I also provide a set of reduced form elasticities at the market level, separately for the wage and employment channels, that can be used as targeted moments.

The remainder of this paper is organized as follows. Section 2 presents the French institutional background and the conceptual framework, with a particular focus on the 2015 reform of wage subsidies. Section 3 describes the data, variables construction and provides summary statistics. Section 4 presents the quasi-experimental research design based on shift-share IV. Section 5 reports causal estimates at the local labor market level. Section 6 identifies the mechanisms driving the wage and employment effects of wage subsidies. Section 7 concludes.

2 Institutional Background and Conceptual Framework

This section begins by providing an overview of wage subsidies in France and the impact of the 2015 reform on their generosity. Next, I develop a simple model of wage subsidies that incorporates equilibrium effects in the labor market, following Rothstein (2010). Finally, I discuss the conditions under which wage and employment effects can be identified from regressions at the local labor market level, showing that this approach is similar to the quasi-experimental shift-share instrumental variable design proposed by Borusyak et al. (2022).

2.1 Wage Subsidies in France

This paper examines wage subsidies targeted at low-earning individuals and households in France. Similar to the U.S. Earned Income Tax Credit (EITC), this government transfer is conditional on employment and was introduced in France in 2001. The main goal is to promote and incentivize employment by increasing financial incentives for working. The French system remained relatively stable until a significant reform was implemented in 2015, affecting incomes from 2016 onward, as explained in more detail below.

The French wage subsidy schedule features both an phase-in segment and a phase-out segment as a function of earnings. The following formula summarizes the level of benefits individuals are eligible for based on their socio-economic characteristics:

$$B_{i,t} = b_t(\mathbf{\Omega}_{i,t}, \boldsymbol{\phi}_t)$$

where $B_{i,t}$ is the amount of benefit for individual i in year t, based on socio-economic characteristics $\mathbf{\Omega}_{i,t} = \{w_i h_i, \boldsymbol{R}_{i,t}, \boldsymbol{D}_{i,t}\}$ and institutional parameters $\boldsymbol{\phi}_t$, which include factors such as eligibility thresholds and parameters for the benefit schedule. Key socio-economic characteristics include an individual's labor earnings, $w_i h_i$ (with w_i representing the hourly wage rate and h_i indicating the number of hours worked), their other household revenues denoted by $\boldsymbol{R}_{i,t}$, and their household characteristics captured by $\boldsymbol{D}_{i,t}$ (such as the number of dependents or marital status, for example). While the exact functional form of b_t varies over time due to policy changes, it generally incorporates these factors to calculate the benefit level.

Context and timing of the reform. Before the 2015 reform, and for incomes earned prior to 2016, two wage subsidy programs were in place in France.

First, there was a tax credit known as the *Prime Pour l'Emploi*, which individuals could claim annually through the income tax system. This tax credit had a one-year delay relative to the income year and was determined by the tax administration using tax returns. Unlike the EITC in the United States, the take-up rate for this tax credit was nearly universal because eligible individuals automatically received it from the tax administration.

Second, an in-work benefit program known as the *Revenu de Solidarité Activité* was provided to individuals through social programs on a monthly basis. This program targeted a lower segment of the earnings distribution than the tax credit program and had a lower take-up rate (approximately 32%, as reported by Bourguignon (2011)). Importantly, any in-work benefits received were subtracted from the income tax credit individuals were eligible for, ensuring that there was no overlap between the two programs.

The government found it inefficient to maintain two programs with similar goals and targeted populations. A report commissioned by the French Prime Minister on wage subsidy reform argued that the two programs "pursued similar objectives" and that "the coexistence of these two mechanisms disperses resources and creates complexity for beneficiaries" (Sirugue, 2013). Therefore, the goal of the 2015 reform was to simplify the French wage subsidy system by creating a single, easily accessible in-work benefit.

Following the 2015 reform—applicable to incomes earned from 2016 onwards—the income tax credit and the in-work benefit were merged into a unique in-work benefit known as the *Prime* *d'Activité*. Individuals receive this wage subsidy through social programs on a monthly basis.[5] Unlike the primary tax credit available before the reform, this new benefit is not automatically distributed to eligible individuals. As a result, the take-up rate decreased, although it remained relatively high at 73% in 2016, as reported by DREES and CNAF (2017).

The timing of the reform was unanticipated and therefore minimizes anticipatory responses, given that the reform was passed in late August 2015 and came into effect in January 2016. Figure B.1 and Figure B.2 display the Google Trends index for each wage subsidy program over time. The search index for the post-reform wage subsidy program remains flat and close to zero before December 2015 but exhibits a sharp increase afterward. This pattern provides further evidence that individuals were likely unaware of the reform until its actual implementation.[6]

Implications of the reform. Figure 1 illustrates the wage subsidy schedules before and after the reform, specifically for the years 2014 and 2017, respectively. It shows the annual amount of wage subsidy that households with various socio-economic characteristics are eligible for, based on a simple simulation where labor earnings are the sole source of income and, in the case of couples, assuming that labor earnings are evenly split between partners. Both panels–panel (a) for single individuals and panel (b) for couples–reveal three key elements. First, the wage subsidy schedule exhibits non-linearity, featuring salient eligibility thresholds, a phase-in segment, and a phase-out segment. Second, there are considerable differences in the wage subsidy schedule depending on an individual's socio-economic characteristics. Finally, the reform introduced substantial variations in the generosity of the wage subsidy schedule, resulting in different changes in thresholds, phase-ins, and phase-outs across socio-economic groups over time.

Overall, the reform increased the generosity of wage subsidies in France. Figure B.3 reproduces the same analysis but expresses the wage subsidy as a percentage of labor earnings. Wage subsidies represent around 62% of labor earnings in the bottom part of the distribution and progressively decrease to 0% around €30,000, depending on the socio-economic characteristics of the household. Post-reform, the schedule shifted to the right, offering more substantial benefits for similar earnings levels. For instance, a single individual with two children earning €15,000 received subsidies equivalent to 35% of their earnings in 2014, which increased to 43% in 2017.

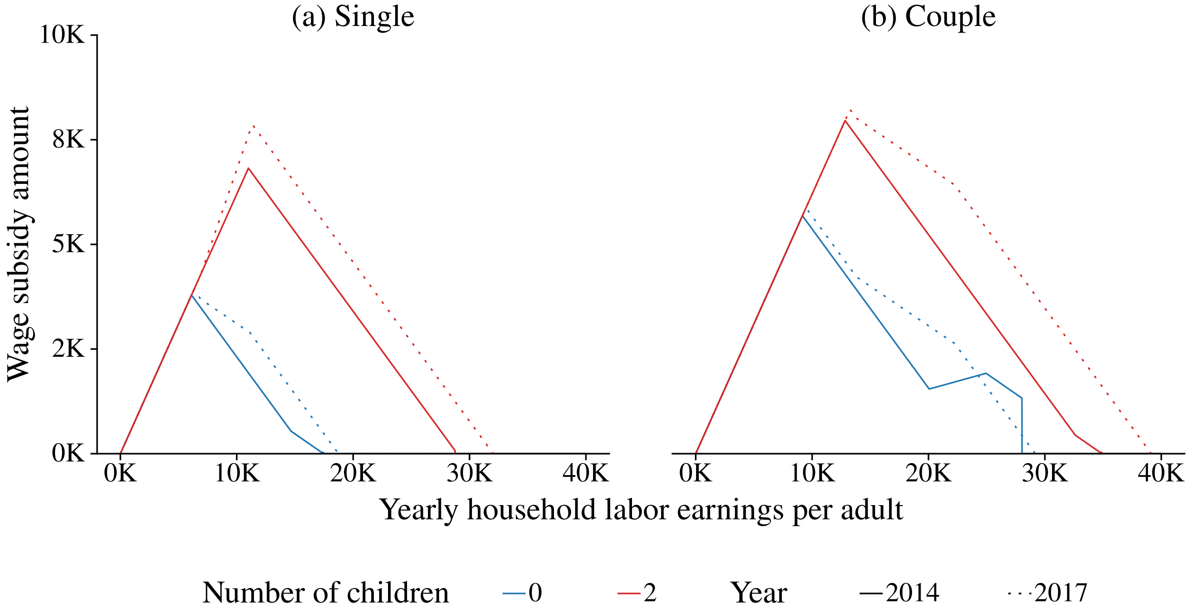
The post-reform wage subsidy program was quickly adopted. Figure B.4 displays the number of households receiving the *Prime d'Activité* and total spending associated with it starting from June 2016. The program already benefited 2.5 million households six months after its introduction, at a monthly cost of €406 million. It has remained relatively stable

[5]While it is paid monthly, the parameters used to compute the benefit are updated quarterly. However, since the data is available only on an annual basis, I cannot fully capture adjustments between different quarters.

[6]Because the *Prime d'Activité* was already in effect, individuals did not receive the *Prime Pour l'Emploi* in 2016 for their 2015 earnings. However, in my empirical strategy, I calculate the amount of tax credit they would have been eligible for, regardless of its actual disbursement. This is because they made their labor supply decisions based on the expected tax credit. This assumption is reasonable given the timing of the reform and the lack of anticipatory effects.

afterward, reaching 2.7 million households two years later in June 2018, at a monthly cost of €444 million.[7] Given the swift adoption of the program and the fact that my sample spans the years 2011 to 2018—including three years after the reform—I am able to estimate the equilibrium responses to changes in wage subsidies.

Figure 1: Wage subsidy schedule, in thousands of euros



Notes: The figure shows the wage subsidy amount a household is eligible for based on its annual household labor earnings per adult, both expressed in thousands of euros. Panel (a) focuses on single individuals, while panel (b) focuses on couples. In each panel, the wage subsidy schedule is shown separately for households with different numbers of children (no children in blue and two children in red) and for two different years (solid lines for 2014 and dotted lines for 2017). The wage subsidy reform was implemented for incomes starting in 2016. The simulation uses OpenFisca, an open-source taxes and benefits simulator. It assumes labor earnings are the sole source of income, that earnings are evenly distributed between partners in a couple, and that there is full take-up of wage subsidy programs.

French labor market. Understanding the French labor market is crucial for interpreting the effects of a reform in wage subsidies. The French labor market has shown high participation rates for both men and women since the early 1990s. Figure B.5 indicates that male participation rates in France, the UK, and the US are similar, ranging from 90% to 95%. For women, participation has significantly increased in France and the UK, reaching 80% to 85% by 2019, while it has stagnated around 75% in the US.

Gender disparities are more pronounced for part-time employment, as illustrated in Figure B.6. Men predominantly work full-time, whereas women are more likely to work part-time.

[7]December 2018 shows a significant increase in the number of households following the Yellow Vests movement in November–December 2018 and President Macron's announcement on December 18th of an increase in the *Prime d'Activité* introduced in January 2019. Leroy (2024) studies this reform in the context of an overall increase in the take-up rate of this program. This reform is beyond the scope of this paper because my sample ends in 2018. My results are robust to analyses excluding 2018.

In 2019, the share of women in part-time employment was 10% in the US, 20% in France, and 30% in the UK.

A possible explanation for these differences is the cost of childcare. Figure B.7 shows that childcare costs for households with two children, as a percentage of net household income, are relatively low in France (about 10% for both single parents and couples). In contrast, these costs are significantly higher in the US (around 40% for single parents and 20% for couples), with the UK falling in between.

2.2 A Simple Model of Wage Subsidies with Equilibrium Effects

Agents. Individuals differ along two key dimensions: the local labor market to which they belong, indexed by $l = 1, \ldots, L$, and their socio-economic group, indexed by n. Socio-economic groups are independent of local labor market conditions and are functions of individual labor earnings, total household income, marital status and number of children. They collectively determine the level of taxes and benefits each group face, making these socio-economic groups proxies for the intensity of treatment from wage subsidy reforms.

Labor demand. I follow closely Rothstein (2010) and assumes that labor is the only input factor used in production. Both the output and labor markets operate under perfect competition. A representative firm produces output F using a constant elasticity of substitution (CES) production function across different local labor markets. The firm's profit maximization problem is:

$$\max_{\{H_k\}_k} \pi = \left(\sum_{k=1}^{L} \beta_k H_k^{\frac{1+\eta}{\eta}} \right)^{\frac{\eta}{1+\eta}} - \sum_{k=1}^{L} w_k H_k$$

The first component represents production F, and the second component represents the cost associated with it. w_k and H_k are the wage rate and labor demand (in hours) in labor market k, and $\eta < 0$ is the elasticity of substitution between different local labor markets. The labor demand for local labor market l is $H_l = \varphi(\boldsymbol{w})^{-1} \beta_l^{-\eta} w_l^{\eta}$, where $\varphi(\boldsymbol{w})$ is an aggregate demand component common to all labor markets. It depends on the wage rates across all markets and adjusts to equate aggregate supply and demand.

Labor supply. Individuals who want to participate and be employed in the labor market incur an entry cost $q_{l,n}$. Once they decide to participate, they then choose the number of hours worked $h_{l,n}$. Individuals maximize their utility, denoted as $U(c_{l,n}, h_{l,n}) = v(c_{l,n}, h_{l,n}) - q_{l,n} 1\left[h_{l,n} > 0\right]$, subject to the budget constraint $c_{l,n} = w_l h_{l,n} - T_n(w_l h_{l,n})$. Here, $c_{l,n}$ represents disposable income and $T_n(w_l h_{l,n})$ represents taxes and benefits, indexed by socio-economic group n due to nationally defined tax schedules. Intuitively, two individuals with similar characteristics (same individual labor earnings, total household income, marital status, and number of children) will have similar taxes and benefits regardless of their location.

The optimal number of hours worked (intensive margin) and participation rate (extensive margin) are respectively equal to $h_{l,n} = h(w_l(1 - \text{MTR}_n))$ and $P_{l,n} = P(w_l h_{l,n}(1 - \text{ATR}_n))$. The optimal hours depend positively on the wage rate and negatively on the marginal tax rate. The participation rate depends positively on labor earnings and negatively on the average tax rate, reflecting the net gain from employment. For simplicity, I assume homogeneity in compensated elasticity of labor supply, denoted as ε^c, and participation elasticity, denoted as ε^p, across all groups.

In a given labor market l, socio-economic group n has $M_{l,n}$ potential workers. The labor supply for group (l, n) is $H_{l,n} = M_{l,n} P_{l,n} h_{l,n}$, and total labor supply in labor market l is $H_l = \sum_n H_{l,n}$.

Wage and employment effects. I define the growth rate of a variable v by $g^v = \Delta \ln(v)$. The growth rates of hours worked and wages at the local labor market level are g_l^H and g_l^w, respectively. At equilibrium, the wage and employment effects of wage subsidies are given by:

$$g_l^w = \alpha^w + \beta^w x_l^{1-MTR} + \gamma^w x_l^{1-ATR} \tag{1}$$

$$g_l^H = \alpha^H + \beta^H x_l^{1-MTR} + \gamma^H x_l^{1-ATR} \tag{2}$$

where x_l^{1-MTR} and x_l^{1-ATR} are the labor market's exposure to changes in the net-of-marginal-tax rate and net-of-average-tax rate, respectively:

$$x_l^{1-MTR} = \sum_n s_{l,n} g_n^{1-MTR} \quad \text{and} \quad x_l^{1-ATR} = \sum_n s_{l,n} g_n^{1-ATR},$$

with $s_{l,n} = H_{l,n}/H_l$ being the share of socio-economic group n in total labor supply of local labor market l. The parameters α^w and α^H are common shocks to all local labor markets. The parameters of interest are the labor market level elasticities β^w, β^H, γ^w, and γ^H, which themselves depend on a set of structural parameters and can be estimated using linear regressions.[8]

This result emphasizes how changes in wage subsidies can affect wages and employment beyond individual-level responses. Feedback effects occur when individual employment decisions collectively influence market wages due to equilibrium responses at the local labor market level. The overall response depends on the hours-weighted sum of net-of-tax rate (one minus the marginal tax rate) and net-of-participation-tax rate (one minus the average tax rate) growth rates defined at the socio-economic group level.

Heterogeneous labor demand. Previously, I assumed perfect substitutability between workers within local labor markets, implying a single wage rate for all workers in a market. I now relax this assumption by introducing heterogeneous labor demand across socio-economic

[8]More precisely, $\beta^w = \varepsilon^c(1 + \varepsilon^p)/\chi, \gamma^w = \varepsilon^p/\chi, \beta^H = \eta\beta^w, \gamma^H = \eta\gamma^w$ with $\chi = \eta - \varepsilon^c - \varepsilon^p - \varepsilon^c\varepsilon^p$, $\alpha^w = (1/\chi)g^\varphi$ and $\alpha^H = [(\eta - \chi)/\chi]g^\varphi$.

groups within each local labor market. The firm produces according to a nested CES production function, with $\eta < 0$ representing the elasticity of substitution between labor markets, and $\eta_l < 0$ representing the elasticity of substitution between socio-economic groups within labor market l. The variables $w_{l,n}$ and $H_{l,n}$ denote the wage rate and labor demand in labor market l for socio-economic group n, respectively. Details about the firm's problem are available in Section C.2.

The average wage rate in local labor market l is $w_l = (\sum_n w_{l,n} H_{l,n})/H_l$, where the aggregate labor supply is $H_l = \sum_n H_{l,n}$. Using a similar approach as in the homogeneous labor demand model, I express the wage and employment effects of wage subsidies at the local labor market as:

$$g_l^w = \alpha_l^w + \sum_n \beta_{l,n}^w s_{l,n} g_n^{1-MTR} + \sum_n \gamma_{l,n}^w s_{l,n} g_n^{1-ATR} \tag{3}$$

$$g_l^H = \alpha_l^H + \sum_n \beta_{l,n}^H s_{l,n} g_n^{1-MTR} + \sum_n \gamma_{l,n}^H s_{l,n} g_n^{1-ATR} \tag{4}$$

with $s_{l,n} = H_{l,n}/H_l$ being the share of socio-economic group n in total labor supply of labor market l, and α_l^w and α_l^L are market-specific components.

Equations (3) and (4) show that changes in wage subsidies have heterogeneous treatment effects on wages and employment across labor markets and socio-economic groups. In this context, Borusyak et al. (2022) and Borusyak and Hull (2024) argue that regressions corresponding to equations (1) and (2) estimate a convexly weighted average of these heterogeneous treatment effects when the shocks g_n^{1-MTR} and g_n^{1-ATR} are quasi-randomly assigned. For example, β^w is a weighted average of coefficients $\beta_{1,1}^w, \ldots, \beta_{k,n}^w, \ldots, \beta_{L,N}^w$, with a positive weight assigned to each of them. In Section 4, I show that my shift-share IV research design relies on a model of instrument assignment such that heterogeneous treatment effects pose no threat to identification.

Alternative model. Kroft et al. (2020) develop a discrete occupational choice framework to include both endogenous wages and involuntary unemployment. In this setting, individuals choose among various occupations, each with its own pre-tax wage and corresponding tax rate. A tax reduction raises labor supply at both the intensive and extensive margins, while equilibrium wages and unemployment adjust in response to shifts in labor supply and firms' vacancy-creation decisions. This generates distinct "micro" and "macro" elasticities of participation and employment, and it is not evident *a priori* whether micro elasticities exceed macro elasticities.

If the tax cut for low-income workers triggers substantial individual entry into the labor market but firms do not expand vacancies enough to absorb this influx, the observed macro-level employment change is smaller than the implied micro-level participation elasticity. Conversely, if wage-setting and vacancy decisions generate "wage moderation"–firms restrain pre-tax wage growth, making it profitable to post more vacancies–then aggregate employment gains can surpass the incremental labor supply observed at the individual level. The wage effect can be negative in both cases.

Overall, local labor market wage and employment effects are still consistently estimated using equations (1) and (2). In particular, my research design does not depend on a specific labor market model. Instead, it leverages the quasi-random assignment of tax shocks across socio-economic groups. I elaborate on this point below.

Income effects. The two previous models have not explicitly discussed potential income effects, which would reduce employment following an increase in wage subsidy generosity. In the taxation literature, income effects are often estimated using variations in one minus the average tax rate or virtual income. Recent studies generally find these effects to be negligible or statistically insignificant (Gruber & Saez, 2002; Kleven & Schultz, 2014; Creedy et al., 2018). Therefore, I do not explicitly address income effects in the remainder of this paper. If present, they are incorporated within the wage and employment elasticities with respect to one minus the average tax rate.

2.3 Intuition for Identification

Building on the French institutional context and the conceptual framework developed above, I discuss the conditions under which the wage and employment effects of wage subsidies can be identified using reduced-form formulas. A valid research design relies on three main assumptions.

First, substitutability among socioeconomic groups in the labor market. This means that employers view workers from different socioeconomic groups as at least partial substitutes for one another within local labor markets. This assumption allows for the labor supply decisions of individuals in response to wage subsidy shocks to spill over to other groups through labor market equilibrium effects. While perfect substitutability is not required–as demonstrated by the model with heterogeneous labor demand–a minimal level of substitutability ensures that changes affecting one group can influence the broader labor market.

Second, local labor markets should be relatively closed or isolated. This assumption implies limited mobility of workers across local markets, ensuring that the labor market equilibrium can be analyzed at the level of the chosen clustering unit. Isolated markets help capture the relevant spillover effects within the market and prevent external shocks from confounding the analysis.

Third, the validity of the research design relies on the quasi-random assignment of exposure to changes in marginal and average tax rates across markets. This means that changes in wage subsidies should not be strategically chosen based on changes in local labor market trends or in a way that correlates with such changes. This assumption is plausible in the French case, where wage subsidy schedules are established at the national level and are not tailored to specific local labor market conditions.

These assumptions are discussed in detail in Section 4. In particular, I demonstrate that this analysis is akin to a shift-share research design, as described by Borusyak et al. (2022), when the wage subsidy schedule is defined at the national level. The shift-share design leverages variation arising from the interaction of national policy changes and differences in local labor markets socio-economic composition, providing a credible identification strategy under the assumptions outlined above.

The magnitude of the response to wage subsidy shocks–the market-level elasticity–depends on a combination of structural parameters, including the elasticity of substitution, the participation elasticity, and the compensated elasticity of labor supply. More generally, we expect that an increase in wage subsidies positively affect employment through increased labor force participation (extensive margin) and potentially more hours worked (intensive margin), but negatively affect wages due to equilibrium effects in the labor market. As labor supply increases in response to subsidies, the increased competition among workers may put downward pressure on wages, especially if labor demand is not perfectly elastic.

Finally, when the take-up of wage subsidies is incomplete–as is the case in France–the research design identifies an intention-to-treat (ITT) effect. The ITT effect measures the impact of offering the wage subsidy to the eligible population, regardless of actual utilization. This is a relevant policy parameter because it reflects the average effect of the policy as implemented. The ITT effect provides a conservative estimate of the policy's impact on those who comply, as it includes both compliers and non-compliers in the analysis. Specifically, the relationship between the ITT and LATE can be expressed as LATE = ITT/take-up rate. Since the take-up rate is less than one, the ITT serves as a lower bound for the LATE.

3 Data, Variables Definition and Summary Statistics

This section provides an overview of the data, describes the construction of the key variables for the analysis, and presents summary statistics. For clarity, I use the same index notation as Borusyak et al. (2022): individuals are indexed by i, local labor markets by l, socio-economic groups by n, and calendar years by t. Additional details about the data and the construction of the variables are available in Appendix D.

3.1 Data

Data. The main data source is the *Echantillon Démographique Permanent* (EDP), a large individual-level panel covering approximately 4% of the French population, randomly sampled. The EDP is a rich dataset that links several administrative records with census information, providing a comprehensive view of individuals' socio-economic characteristics. I use two administrative datasets from the EDP. First, the matched employer-employee dataset: the *DADS* (Déclaration annuelle des données sociales) provides detailed information on individuals' hours worked and their contract types.[9] Unfortunately, firm identifiers are not available in this dataset. Second, I use data on individual and household incomes derived from income tax returns. This includes information on labor earnings, capital income, unemployment benefits, taxes, and tax credits.

Sample. My analysis focuses on the labor market equilibrium effects of wage subsidies. To address this question, I construct the main sample through the following steps.

First, I focus on working-age individuals aged 25 to 55 and residing in metropolitan France in a given year, during the period from 2011 to 2018. This age range captures individuals most likely to participate actively in the labor force, excluding younger individuals who may be in education and older individuals approaching retirement. I include individuals for whom the tax household can be accurately identified. This encompasses single individuals living independently and couples who are married or in a civil union. This restriction is necessary because the French tax and benefit system is based on household characteristics, such as marital status and the number of dependents, which are crucial for precisely computing taxes and benefits.

Second, my analysis involves constructing growth rates for several labor market outcomes and tax shocks between an initial year t and a subsequent year $t + h$. In the baseline analysis, I compute three-year growth rates ($h = 3$). The initial year t ranges from 2011 to 2015, with 2015 being the last year of earnings before the reform. Therefore, I have five time periods: 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018.[10] Each observation corresponds to an individual observed in both the initial year t and the subsequent year $t + h$. For instance, an individual observed in both 2015 and 2018 constitutes an observation. To address potential sample attrition and ensure robustness, I also conduct analyses using two-year growth rates ($h = 2$) while maintaining the same range for the initial year t.

Finally, I restrict the sample to individuals who are low-wage earners, defined as those whose pre-tax hourly wage rate is below €14 per hour in the initial year t.[11] This condition excludes high-income earners who likely participate in a very different labor market than those targeted by the wage subsidy program in France. It still includes a large portion of the French population, including those not eligible to the program.[12] The results are robust to alternative thresholds, such as €14.50 and €15 per hour.

[9] Regarding the concepts of main activity and main firm, they refer to situations where an individual has multiple employment spells in different firms within a given year. In such cases, the type of contract, occupation, sector, and number of workers correspond to those of the longest spell (or the highest paying one in cases of equivalent durations).

[10] I discuss the implications of a stacked sample in Section 4.

[11] I impose not restriction on the pre-tax hourly wage rate in subsequent year $t + h$ to avoid censored growth rates.

[12] This threshold is based on data from INSEE, where the average hourly wage for full-time workers is €14.15. The sixth, seventh, and eighth deciles are €12.54, €14.21, and €16.94, respectively. Note that INSEE uses net labor earnings after social contributions, which are slightly lower than taxable labor earnings, as the latter include some forms of social contributions.

Additional data. First, I complement the main data with the Population Census. This dataset provides detailed information on commuting patterns, including individuals' places of residence and places of work for a sample of the population each year. Additional information on the Population Census and sample selection can be found in Section D.3.

Second, I use firm-level data from the FARE dataset, an administrative fiscal dataset covering all firms operating in France from 2011 to 2018. It includes detailed information on firms' production activities, financial statements, employment levels, and other economic indicators. I restrict the sample to firms with positive value-added and more than five full-time equivalent employees. This criterion ensures that the analysis focuses on active firms of a meaningful economic size, enhancing the reliability of local labor market level outcomes.

3.2 Variables Definition

Local labor markets definition. I adopt a simple decomposition based on individuals' geographic residence. I categorize individuals into *départements*, which are administrative divisions in France comprising 101 geographical areas. Due to data limitations, my focus narrows down to 94 départements.[13] This decomposition maximizes the number of observations within each location while preserving variation in labor market characteristics necessary for the implementation of the identification strategy.

A potential concern is that using départements may be too coarse a definition of local labor markets. To address this, I test the robustness of my results using commuting zones defined by the French National Institute of Statistics and Economic Studies (INSEE) in 2010 as an alternative definition of local labor markets. These zones, where most of the labor force lives and works, satisfy the assumption of distinct and closed labor markets by design.[14] My sample includes 297 unique commuting zones per period.[15] However, due to sampling and observation restrictions, commuting zones have fewer individuals than départements on average, making variables potentially more sensitive to outliers and a within local labor market analysis more difficult. Table A.1 displays the distribution of the number of individuals across local labor market-year cells: a commuting zone-period cell contains on average 602 individuals versus 1,902 for a département-period cell. Nevertheless, the results remain quantitatively similar under both definitions, validating the use of départements as a good proxy for local labor

[13]Overseas départements and the two départements in Corse are excluded from my analysis due to insufficient observations in my dataset.

[14]The INSEE defines a commuting zone as "a geographical area within which most of the labour force lives and works. The division into labour market area provides a breakdown of the territory adapted to local studies on employment."

[15]There are 96 *départements* in mainland France (101 including overseas), each averaging 5,666km^2 (543,908.3km^2/96) (see INSEE), and 304 commuting zones, each averaging 1,789km^2 (543,908.3km^2/304). In comparison, the United States (50 states plus D.C.) has 3,143 counties, each averaging 2,910km^2 (9,147,593km^2/3,143), and 709 commuting zones (2000 definitions), each averaging 12,902km^2 (see CIA World Factbook). Consequently, a *département* is roughly twice the size of an average U.S. county. Overseas *départements* and the two *départements* in Corsica are excluded from my analysis due to insufficient observations in the dataset, reducing the number of *départements* to 94 and the number of commuting zones to 297.

markets.

Socio-economic groups definition. In Section 2, I described the main important variables for calculating wage subsidies in France. It primarily relies on an individual's labor earnings, additional household income, marital status, and the number of dependents.

First, I construct an equalized measure of household income, computed as the sum of household-level labor earnings. In cases where individuals are part of a couple, this sum is divided by 2. For individuals who are not employed, I incorporate their predicted labor earnings based on their socio-economic characteristics into the overall household labor earnings. Details about the imputation procedure are available in Section D.4. Then, I split this measure into bins of 1,000 euros, ranging from 0 to 30,000 euros (with the final bin contains all individuals whose income is above this threshold). Second, I construct binary indicators for being in a couple and for having children. Finally, I define a socio-economic group as the interaction of a household labor earnings bin, the binary indicator for couples, and the binary indicator for individuals with children.

Labor market outcomes. The analysis involves a set of growth rates of labor market outcomes measured at the labor market level l. To derive these measures, I use individuals' residence in the initial period t to define their local labor markets to avoid any composition effects that may introduce measurement bias. The outcomes are not sensitive to this definition, as most individuals remain in the same labor market between t and $t + h$. For clarity, I omit the socio-economic group index n in this paragraph.

First, I observe the number of hours worked $h_{i,l,t}$, the average hourly wage rate $w_{i,l,t}$, and the taxable labor earnings $w_{i,l,t}h_{i,l,t}$ for each individual, indexed by i, residing in local labor market l in year t.[16] All monetary outcomes are in real terms, with a base year of 2011.

Second, I define the labor supply, total earnings and average hourly wage rate at the local labor market level by:

$$H_{l,t} = \sum_{i\in(l,t)} h_{i,l,t}, \quad E_{l,t} = \sum_{i\in(l,t)} w_{i,l,t}h_{i,l,t}, \quad w_{l,t} = \frac{E_{l,t}}{H_{l,t}}.$$

Finally, I define three sets of outcomes at the local labor market level: the log-growth rate in the total number of hours worked, $g^H_{l,t}$; the log-growth rate in the average hourly wage rate, $g^w_{l,t}$; and the log-growth rate in total earnings, $g^E_{l,t}$.[17] These are observed between time periods t and

[16]It excludes employer social contributions and most employee social contributions. I exclude employer social contributions and most employee social contributions from labor earnings. For each year and conditional on working, hours worked are winsorized at the upper 98th percentile. Similarly, the hourly wage rate is winsorized at the lower 1st percentile in the base year t, and at both the lower 1st and upper 99th percentiles in $t + h$. Note that the hourly wage is already capped at €14 per hour due to the sample construction. Labor earnings are then calculated as the product of these two winsorized variables.

[17]Because I classified individuals based on their location in the initial period t, the growth rates are calculated for those who were initially in local labor market l in year t to avoid any composition effects. Since most individuals

$t + h$, and are indexed by the initial year t for clarity:

$$g^H_{l,t} = \ln(H_{l,t+h}) - \ln(H_{l,t}), \quad g^w_{l,t} = \ln(w_{l,t+h}) - \ln(w_{l,t}), \quad g^E_{l,t} = \ln(E_{l,t+h}) - \ln(E_{l,t}).$$

By definition, the growth rate in total earnings is the sum of the growth rate in the total number of hours worked and the growth rate in the average hourly wage rate, such that $g^E_{l,t} = g^H_{l,t} + g^w_{l,t}$. In my baseline analysis, I compute three-year log-growth rates ($h = 3$).

Tax rates and shocks. My research design relies on tax shocks defined at the national level that vary across socio-economic groups. More precisely, it involves the log-growth rates between between t and $t + h$ of the net-of-participation-tax rate $g^{1-ATR}_{n,t}$ and the net-participation-tax rate $g^{1-MTR}_{n,t}$ for each socio-economic group n. To derive these measures, I use individuals' socio-economic characteristics in the initial period t to define their socio-economic groups, thereby avoiding any composition effects that may introduce measurement bias. I omit the labor market index l for simplicity.

Although taxes and benefits are available in the main dataset, marginal and average tax rates are not. I generate these rates using a publicly available tax and benefit simulator for France.[18] To account for the impact of an increase in wage subsidies, I compute the marginal and average tax rates for each individual i in socio-economic group n in year t, assuming full take-up of taxes and benefits. Consequently, my findings should be interpreted as intention-to-treat effects, as discussed in Section 2. I derive the marginal tax rate $\text{MTR}_{i,n,t}$ and the average tax rate $\text{ATR}_{i,n,t}$ using the full tax and benefit system, accounting for the fact that changes in labor market participation and earnings might also affect eligibility and amounts received from other programs.

Next, for each individual i, I compute the log-growth rate of their net-of-tax rate (one minus the marginal tax rate) and their net-of-participation-tax rate (one minus the average tax rate) between year t and year $t + h$. For example, the log-growth of the net-of-tax rate is given by:

$$g^{1-MTR}_{i,n,t} = \ln\left[1 - \text{MTR}_{i,n,t+h}(\boldsymbol{\Omega}_{i,n,t+h}, \boldsymbol{\phi}_{t+h})\right] - \ln\left[1 - \text{MTR}_{i,n,t}(\boldsymbol{\Omega}_{i,n,t}, \boldsymbol{\phi}_t)\right],$$

where, following the notation from Section 2, $\boldsymbol{\Omega}_{i,n,t} = \{w_i h_i, \boldsymbol{R}_{i,n,t}, \boldsymbol{D}_{i,n,t}\}$ represents socio-economic characteristics, and $\boldsymbol{\phi}_t$ includes institutional parameters like eligibility thresholds and benefit schedule parameters for year t. Key socio-economic characteristics include an individual's labor earnings $w_i h_i$ (with w_i as the hourly wage rate and h_i as the number of hours worked), other household revenues $\boldsymbol{R}_{i,n,t}$, and household characteristics $\boldsymbol{D}_{i,n,t}$ (such as number of dependents or marital status). The log-growth rate for the net-of-participation-tax rate is constructed similarly, replacing the marginal tax rate with the average tax rate in the formula.

A substantial body of literature highlights challenges when directly regressing labor market

largely remain in the same local labor market over time, my results are not sensitive to this method of computation.

[18] OpenFisca is available at https://fr.openfisca.org/.

outcomes on tax rates defined this way. This is because individuals adjust their labor earnings—by changing hours worked or wage rate—in response to changes in taxes and benefits. Consequently, taxes and benefits become a direct function of labor earnings, introducing reverse causality and threatening identification. To address this issue, I draw on the simulated instruments literature by calculating tax rates under the assumption of no behavioral responses to the reform (e.g., Auten & Carroll, 1999; Moffitt & Wilhelm, 2000; Gruber & Saez, 2002; Kopczuk, 2005; Weber, 2014). Specifically, the simulated change in the net-of-tax rate is:

$$\tilde{g}^{1-\text{MTR}}_{i,n,t} = \ln\left[1 - \text{MTR}_{i,n,t+h}(\boldsymbol{\Omega}_{i,n,t}, \boldsymbol{\phi}_{t+h})\right] - \ln\left[1 - \text{MTR}_{i,n,t}(\boldsymbol{\Omega}_{i,n,t}, \boldsymbol{\phi}_{t})\right],$$

where the marginal tax rate in $t+h$ is now a function of the individual's socio-economic characteristics from period t, $\boldsymbol{\Omega}_{i,n,t}$. Intuitively, this method constructs counterfactual tax rates by simulating the rates without individual behavioral responses, capturing only the mechanical changes in the net-of-tax and net-of-participation-tax rates. Importantly, this change is exogenous to potential changes in the wage rate and the number of hours worked. I adjust labor earnings and other household revenues for inflation using the Consumer Price Index (CPI) between t and $t+h$. Both the observed and simulated individual-level tax shocks are winsorized at the 5th and 95th percentiles each year.

The socio-economic group level observed shocks are a weighted average of individual-level shocks:

$$g^{1-MTR}_{n,t} = \sum_{i\in(n,t)} s_{i,n,t}\, g^{1-MTR}_{i,n,t} \quad \text{and} \quad g^{1-ATR}_{n,t} = \sum_{i\in(n,t)} s_{i,n,t}\, g^{1-ATR}_{i,n,t} \tag{5}$$

where $s_{i,n,t} = h_{i,n,t}/H_{n,t}$ represents the proportion of hours worked by individual i out of the total hours worked in socio-economic group n and initial year t. I construct the simulated shocks $\tilde{g}^{1-MTR}_{n,t}$ and $\tilde{g}^{1-ATR}_{n,t}$ using the same methodology.

I assume that treatment intensity varies among the different socio-economic groups but is not specific to local labor markets, such that shocks at the (l,n,t) level are noisy versions of underlying latent shocks at the (n,t) level. This assumption holds in the French context because the wage subsidy schedule is determined at the national level, ensuring that the shock associated with each initial socio-economic group n is not correlated with specific labor market characteristics by design.[19]

Exposure measures. Then, I define the labor market exposure to shocks defined at the socio-economic group level. The share of the number of hours worked by socio-economic group n in labor market l in initial year t is defined by $s_{l,n,t} = H_{l,n,t}/H_{l,t}$, which varies across local labor

[19]More precisely, $g^{1-MTR}_{l,n,t} = g^{1-MTR}_{n,t} + \nu^{1-MTR}_{l,n,t}$ and $g^{1-ATR}_{l,n,t} = g^{1-ATR}_{n,t} + \nu^{1-ATR}_{l,n,t}$,where $\nu_{l,n,t}$ is an estimation error. For individuals who are not employed in the labor market during the initial period, they are assigned an implicit weight of zero. However, to determine their marginal and average tax rates, I rely on the predicted values for their labor earnings, which are designed to be similar on average to those in their respective socio-economic group. As a result, there are no substantial differences in the tax shocks for this group, given the construction of these variables.

markets due to differences in their socio-economic composition.[20] Consequently, they exhibit varying exposure levels to the same nationwide set of shocks. Formally, distinct labor markets experience varying treatment levels for each period indexed by initial year t:

$$x_{l,t}^{1-MTR} = \sum_{g} s_{l,n,t} g_{n,t}^{1-MTR} \quad \text{and} \quad x_{l,t}^{1-ATR} = \sum_{g} s_{l,n,t} g_{n,t}^{1-ATR} \tag{6}$$

This treatment variable quantifies the labor market's exposure to nationwide shocks in taxes and benefits. For instance, $x_{l,t}^{1-MTR}$ (respectively $x_{l,t}^{1-ATR}$) represents the hours-weighted growth rate in the net-of-tax rate (respectively the net-of-participation-tax rate) for labor market l between t and $t+h$.

I follow the same procedure as with the observed shocks to construct instruments at the local labor market level:

$$z_{l,t}^{1-MTR} = \sum_{g} s_{l,n,t} \tilde{g}_{n,t}^{1-MTR} \quad \text{and} \quad z_{l,t}^{1-ATR} = \sum_{g} s_{l,n,t} \tilde{g}_{n,t}^{1-ATR} \tag{7}$$

3.3 Summary Statistics

Local labor markets. Table 1 summarizes the distribution of key variables at the local labor market level, where local labor markets are defined as départements, for the period from 2011 to 2018. All variables are weighted by the share of the local labor market in the national population in the initial year $t = 2011, \ldots, 2015$. Table A.2 presents the same descriptive statistics using commuting zones as the definition of local labor markets.

First, panel (a) shows the three-year log-growth rates of total labor earnings, total hours worked, average hourly wage rate, and employment rate. On average, labor earnings exhibit positive growth (mean = 7.1%, SD = 1.8%), primarily driven by the positive growth in the average hourly wage rate (mean = 8%, SD = 1.5%).

Next, panel (b) presents a set of labor market variables in the initial (start-of-period) year to provide perspective on the magnitude of these variations. The average labor earnings amount to €17,170 (SD = €517), with an average hourly wage rate of €10.69 (SD = €0.18), and an average number of hours worked (conditional on working) equal to 1,587 (SD = 38). For comparison, the annual number of hours for those working full-time was 1,607 in 2011, with a minimum wage of approximately €12,888.[21] On average, a significant portion of the population is employed (mean = 87%, SD = 5%), works throughout the entire year (mean = 70%, SD = 5%), holds a full-time employment contract (mean = 67%, SD = 5%), and earns wages close to the minimum wage, with an hourly rate less than €1 above the minimum wage (mean = 9%,

[20] Shares are constructed based on the observed numbers of hours for those working in initial year t and predicted number of hours for those not working. See Appendix D for more details.

[21] This calculation assumes a 35-hour workweek for full-time employment. The taxable minimum wage is slightly higher as it incorporates certain social contributions, although the difference is minimal. For a time series on the national minimum wage, see https://www.insee.fr/fr/statistiques/serie/000879878.

SD = 2%). Individuals also tend to work predominantly in services (mean = 58%, SD = 7%), with comparatively fewer employed in industry (mean = 11%, SD = 5%).

Finally, panel (c) presents key demographics in the initial (start-of-period) year. The mean age across local labor markets is 38 years (SD = 1 year), with a significant share being in a couple (mean = 67%, SD = 6%) and having children (mean = 66%, SD = 6%). The average share of individuals eligible to receive wage subsidies is 47% (SD = 6%), which means that my sample captures not only individuals eligible to the program but also others with similar labor market characteristics.

Tax shocks and exposure measures. Section 2 shows that quasi-experimental research design and the validity of my exposure measure rely on the assumption that simulated tax shocks are quasi-randomly assigned (Borusyak et al., 2022). I discuss in more detail this assumption in Section 4. I now describe the distribution of these shocks across socio-economic groups and years, as well as the distribution of the exposure measures across local labor markets and years.

First, I assess the underlying variation in the shift-share IV design by summarizing the shocks at the socio-economic group-period level (Borusyak et al., 2022). Panel (a) of Table 2 displays the distribution of the three-year log-growth of simulated net-of-participation-tax rate shocks ($\tilde{g}_{n,t}^{1-ATR}$) and net-of-tax rate shocks ($\tilde{g}_{n,t}^{1-MTR}$) across socio-economic groups and periods (total observations $N = 620$). All statistics are weighted by the average exposure share $s_{n,t} = \sum_l e_{l,t} s_{l,n,t}$, where $s_{l,n,t}$ is the share of the number of hours worked by socio-economic group n in labor market l in initial year t and $e_{l,t}$ is the share of the national population residing in local labor market l in initial year t. For each set of shocks, I report both their raw distribution and their distribution after residualizing on period fixed effects. Table A.3 reports the same set of summary statistics for observed shocks.

The raw distribution of $\tilde{g}_{n,t}^{1-ATR}$ has a mean of −0.018, a median of −0.018, and a standard deviation of 0.018. Similarly, the raw distribution of $\tilde{g}_{n,t}^{1-MTR}$ has a mean of −0.036, a median of −0.027, and a standard deviation of 0.058. There is substantial variation in tax shocks, with a 6.3 percentage point difference between the 5th and 95th percentiles of the log-growth rates for the net-of-participation-tax rate, and a 18.6 percentage point difference for the net-of-tax rate. After residualizing on period fixed effects, the distributions become symmetric, with means and medians close to zero. This also confirms that substantial variation remains, as the standard deviations are similar to those in the raw distributions.

To better understand the effect of the reform on tax shocks, Figure B.8 and Figure B.9 plot the three-year log-growth rates for the simulated net-of-participation-tax rates and net-of-tax rates, respectively, by socio-economic group and separately for the periods 2011–2014 and 2015–2018. During the 2011–2014 period (before the reform), the tax shocks remain close to zero and stable across all groups.[22] In contrast, during the 2015–2018 period, there

[22]Some variation is still observed in the 2011–2014 period. One major reason is that labor earnings and other forms of income grow over time, so for a wage subsidy schedule that remains constant, the tax shocks tend to be

Table 1: Local labor markets (LLM) summary statistics

	Mean	SD	p5	Median	p95
(a) Three-year log-growth rates					
Labor earnings	0.071	0.018	0.041	0.072	0.098
Hours	-0.009	0.017	-0.039	-0.009	0.016
Wage rate	0.08	0.015	0.06	0.079	0.107
Employment rate	-0.003	0.017	-0.039	0	0.018
(b) Start-of-period labor market characteristics					
Mean labor earnings (in euros)	17,170	517	16,220	17,189	18,109
Mean hours	1,376	100	1,206	1,394	1,536
Mean hours, cond. on working	1,587	38	1,520	1,589	1,643
Mean wage rate (in euros)	10.69	0.18	10.41	10.67	11.02
Mean employment rate	87%	5%	78%	87%	97%
Prop. working full-year	70%	5%	61%	70%	77%
Prop. working full-time	67%	5%	60%	68%	76%
Prop. close to the MW	9%	2%	6%	10%	12%
Prop. working in industry	11%	5%	4%	11%	18%
Prop. working in services	58%	7%	50%	56%	73%
(c) Start-of-period demographics					
Mean age	38	1	37	38	39
Prop. eligible to the wage subsidy	47%	6%	38%	47%	59%
Prop. in a couple	67%	6%	59%	68%	76%
Prop. with children	66%	6%	60%	66%	72%
(d) Sample size					
No. of LLM = 94; No. of periods = 5; No. of LLM-periods = 470.					

Notes: This table provides summary statistics for local labor markets defined as départements. Panel (a) reports the three-year log-growth rates of labor market variables for the five time periods 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018; panel (b) shows characteristics of local labor markets for base years between 2011 and 2015; and panel (c) includes demographic characteristics for base years between 2011 and 2015. Panel (d) presents sample size information. Close to the minimum wage is defined as having an hourly wage rate below the minimum wage plus €1. All statistics are weighted by each local labor market's share in the national population during the initial period. All monetary values are presented in real terms, with a base year of 2011.

is substantial variation in the net-of-participation-tax rate. These changes are particularly significant for households in the lower part of the labor earnings distribution, as they are more exposed to wage subsidies.

Tax shocks are defined to include the full tax and benefit system. One potential concern is that they might capture other variations in taxes and benefits beyond wage subsidies, which

negative.

could correlate with labor market equilibrium responses. To address this concern, Figure B.10 plots the correlation between the tax shocks computed using the full tax and benefit system and those computed using only wage subsidies, across socio-economic groups and periods. Both measures are highly correlated, suggesting that most of the variation comes from changes in wage subsidies. Results from an OLS regression (with intercept) show a correlation coefficient of 0.86 for the net-of-tax rate and 0.76 for the net-of-participation-tax rate.

Second, panel (b) of Table 2 displays the distribution of the exposure measures for the simulated net-of-participation-tax rates ($z_{l,t}^{1-ATR}$) and net-of-tax rates ($z_{l,t}^{1-MTR}$) across local labor markets and periods (total observations $N = 470$). All statistics are weighted by the share of local labor market l in the national population in the initial year t, denoted $s_{l,t}$. Similar to the tax shocks, I report both the raw distributions and those after residualizing on period fixed effects for each set of exposure measures.

The raw distribution of $z_{l,t}^{1-ATR}$ has a mean of -0.018, a median of -0.022, a standard deviation of 0.009, and a 3.4 percentage point difference between the 5th and 95th percentiles of the log-growth rates. For $z_{l,t}^{1-MTR}$, the mean is -0.036, the median is -0.03, the standard deviation is 0.015, and there is a 8.8 percentage point difference between the 5th and 95th percentiles. After residualizing on period fixed effects, the distributions become symmetric, with means and medians equal to zero. This also confirms that substantial variation remains, with a 0.6 percentage point difference between the 5th and 95th percentiles for the net-of-participation-tax rate and a 1.2 percentage point difference for the net-of-tax rate.

The reform is the major source of variation across local labor markets over time. Figure B.11 and Figure B.12 plot the exposure measures for the net-of-participation-tax rate and net-of-tax rate, respectively, across local labor markets, separately for the periods 2011–2014 (panel (a)) and 2015–2018 (panel (b)). The 2011–2014 period (before the reform) features small exposure measures close to zero, while the exposure measures for the 2015–2018 period are particularly sizeable. This confirms that my exposure measures effectively capture variations in wage subsidies.

Finally, I report summary statistics for the sample size in panel (c). The effective sample size, as measured by the inverse Herfindahl index ($1/\sum_{n,t} s_{n,t}^2$), is 243. This confirms that the effective sample size is large (Borusyak et al., 2022). Consistent with this result, the largest share accounts for less than 1%.

4 Quasi-Experimental Research Design

In this section, I develop a shift-share IV design, based on Borusyak et al. (2022), to assess the causal labor market equilibrium effects of a change in wage subsidies. I begin by showing that the variations in the shifts–or shocks–across local labor markets resulting from a nationwide wage subsidy reform stem from two key factors. First, differences in the initial exposure to the reform due to the heterogeneous socio-economic composition of local labor markets. Second,

Table 2: Simulated tax shocks and exposure measures summary statistics

	Mean	SD	p5	Median	p95	N
(a) Socio-economic groups: three-year tax shocks						
Net-of-participation-tax rates:						
$\tilde{g}_{n,t}^{1-ATR}$	-0.018	0.018	-0.052	-0.018	0.011	620
$\tilde{g}_{n,t}^{1-ATR}$ (resid. on period F.E)	0	0.016	-0.028	0.001	0.026	620
Net-of-tax rates:						
$\tilde{g}_{n,t}^{1-MTR}$	-0.036	0.058	-0.142	-0.027	0.044	620
$\tilde{g}_{n,t}^{1-MTR}$ (resid. on period F.E)	0	0.057	-0.097	0.007	0.075	620
(b) Local labor markets: three-year exposure measures						
Net-of-participation-tax rates:						
$z_{l,t}^{1-ATR}$	-0.018	0.009	-0.028	-0.022	-0.006	470
$z_{l,t}^{1-ATR}$ (resid. on period F.E)	0	0.002	-0.003	0	0.003	470
Net-of-tax rates:						
$z_{l,t}^{1-MTR}$	-0.036	0.015	-0.067	-0.03	-0.021	470
$z_{l,t}^{1-MTR}$ (resid. on period F.E)	0	0.004	-0.006	0	0.006	470
(c) Sample size						
Distribution of shares $s_{n,t}$:						
Effective sample size (1/HHI) = 243						
1/HHI across SE groups = 49						
Largest share = 0.86%						
Observation counts:						
No. of LLM = 94; No. of SE groups = 124; No. of periods = 5.						

Notes: This table summarizes the distribution of simulated tax shocks and instruments over the the five time periods 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018. Panel (a) reports the distribution of shocks across socio-economic groups, panel (b) presents the distribution of instruments for the exposure measures across local labor markets, and panel (c) provides the sample size. In both panels (a) and (b), statistics are reported separately for the net-of-participation-tax rates and the net-of-tax rates. Shocks and exposures are also residualized on period fixed effects. Shocks and exposures are calculated as three-year log differences, with base year t ranging from 2011 to 2015. Statistics in panel (a) are weighted by the shares $s_{n,t}$, and those in panel (b) are weighted by the shares $s_{l,t}$, representing each local labor market's share in the national population.

exogenous shocks to wage subsidies defined at the national level. I then define the conditions under which this research design identifies the wage and employment effects of wage subsidies.

4.1 Estimation

Setting. I closely follows the notation of Borusyak et al. (2022). Specifically, local labor markets are indexed by l, socio-economic groups by n, and calendar years by t. Log-growth rates defined between t and $t + h$, where h is the horizon, are indexed by the initial year t.

Following the data construction detailed in Section 3, I observe three outcomes at the local labor market level: the growth rate in the total number of hours worked, $g^H_{l,t}$; the growth rate in the average hourly wage rate, $g^w_{l,t}$; and the growth rate in total earnings, $g^E_{l,t}$. I denote any one of these outcomes by $y_{l,t}$. I also observe two treatment variables–or exposure measures–$x^{1-MTR}_{l,t}$ and $x^{1-ATR}_{l,t}$, along with their corresponding instruments. The two instruments are defined as:

$$z^{1-MTR}_{l,t} = \sum_n s_{l,n,t}\tilde{g}^{1-MTR}_{n,t} \quad \text{and} \quad z^{1-ATR}_{l,t} = \sum_n s_{l,n,t}\tilde{g}^{1-ATR}_{n,t},$$

where $\tilde{g}^{1-MTR}_{n,t}$ and $\tilde{g}^{1-ATR}_{n,t}$ are the simulated net-of-tax rate shocks and net-of-participation-tax rate shocks for socio-economic group n, respectively. The weights $s_{l,n,t} \geq 0$ define the exposure of each local labor market l to shocks at the socio-economic group level n, and these exposure weights sum to one: $\sum_n s_{l,n,t} = 1$. Finally, I observe a set of control variables summarized by the column vector $\mathbf{\Lambda}_{l,t}$.

Specification. I estimate the following two-stage least squares (2SLS) regression:

$$y_{l,t} = \beta x^{1-MTR}_{l,t} + \gamma x^{1-ATR}_{l,t} + \mathbf{\Lambda}'_{l,t}\boldsymbol{\theta} + \epsilon_{l,t}. \tag{8}$$

The coefficients of interest, β and γ, respectively represent the causal effects of changes in the local labor market level net-of-tax rate and net-of-participation-tax rate. To address the reverse causality concern—where tax shocks might be directly influenced by local labor market outcomes—I instrument $x^{1-MTR}_{l,t}$ and $x^{1-ATR}_{l,t}$ with $z^{1-MTR}_{l,t}$ and $z^{1-ATR}_{l,t}$. These instruments isolate the exogenous variation in tax rates, ensuring that the estimated effects are indeed causal. Each observation is weighted by the share of the national population residing in local labor market l in initial year t, denoted $e_{l,t}$.

Equivalent shock-level IV regression. To further discuss the source of identification arising from the quasi-random assignment of shocks $\tilde{g}^{1-MTR}_{n,t}$ and $\tilde{g}^{1-ATR}_{n,t}$, I define the equivalent shock-level IV regression following Borusyak et al. (2022):

$$\bar{y}_{n,t} = \beta\bar{x}^{1-MTR}_{n,t} + \gamma\bar{x}^{1-ATR}_{n,t} + \bar{\mathbf{\Lambda}}'_{n,t}\boldsymbol{\theta} + \bar{\epsilon}_{n,t}, \tag{9}$$

where each variable $\bar{v}_{n,t}$ denotes an exposure-weighted average of variable $v_{l,t}$ using the following formula: $\bar{v}_{n,t} = (\sum_l e_{l,t}s_{l,n,t}v_{l,t})/(\sum_l e_{l,t}s_{l,n,t})$. I instrument $\bar{x}^{1-MTR}_{n,t}$ and $\bar{x}^{1-ATR}_{n,t}$ with $\tilde{g}^{1-MTR}_{n,t}$ and $\tilde{g}^{1-ATR}_{n,t}$. The set of controls $\bar{\mathbf{\Lambda}}_{n,t}$ is at the socio-economic group level. Each observation is weighted by $s_{n,t} = \sum_l e_{l,t}s_{l,n,t}$.

Equations (8) and (9) are strictly equivalent and produce the same estimates of β and γ (Borusyak et al., 2022). In practice, I follow Borusyak et al. (2022) and first residualize the outcome $y_{l,t}$ and the observed exposure measures $x^{1-MTR}_{l,t}$ and $x^{1-ATR}_{l,t}$ on the set of local labor market controls $\mathbf{\Lambda}_{l,t}$ (including local labor market and period fixed effects, for example) using equation (8). Then, I construct the exposure-weighted average of each of these residualized variables. Finally, I use these shock-level variables to estimate equation (9), including shock-level controls such as socio-economic group fixed effects.

The shock-level regression is also useful for estimating exposure-robust standard errors. Standard errors computed from equation (8), whether heteroskedasticity-robust or clustered at the local labor market level, tend to overreject the null hypothesis of no effect (Adao et al., 2019; Borusyak et al., 2022). This is because when two local labor markets have similar socio-economic shares, they will not only have similar exposure measures but also similar unobserved values $\nu_{n,t}$ in the error term $\epsilon_{l,t}$. This creates mutual dependencies between the shocks $x_{l,t}^{1-MTR}$ and $x_{l,t}^{1-ATR}$ and the error term $\epsilon_{l,t}$ across observations with similar exposure shares. Using equation (9) allows for inference and testing that circumvent this problem. I report standard errors clustered at the socio-economic group level because my sample stacks multiple periods indexed by the initial year $t = 2011, \ldots, 2015$, such that errors could be correlated across socio-economic groups over time.

Controls. Heterogeneous growth rates of labor market outcomes–such as employment, wage rates, and labor earnings–occur across the population. For example, individuals living in Paris are more likely to experience higher growth rates than those in the south of France. Similarly, local labor markets with already high average wage rates are potentially less likely to have high wage growth rates. If ignored, these components could be confounding factors that threaten the empirical strategy.

To estimate consistent coefficients, I introduce a set of controls widely used in the taxation literature (Gruber & Saez, 2002; Kopczuk, 2005; Giertz et al., 2008; Kleven & Schultz, 2014; Weber, 2014). The baseline specification includes several key elements. First, local labor market fixed effects that absorb differential trends across markets. Second, period fixed effects that control for period-specific unobservable shocks, such as those due to the business cycle. Third, base-year (start-of-period) controls at the local labor market level that influence growth rates of labor market outcomes, such as the average number of hours worked and wage rates across individuals. Finally, socio-economic group fixed effects that absorb differential trends across socio-economic groups at the national level.[23] For example, Guvenen et al. (2021) shows that average log-growth rates of labor earnings are heterogeneous along the initial labor earnings distribution. I test various combinations and specifications of these controls in the robustness tests.

[23]The inclusion of socio-economic group fixed effects is possible thanks to the equivalent shock-level IV regression defined by equation (9). The average number of hours worked across individuals in a local labor market includes those with a value of zero (not working), thus capturing confounders from both extensive and intensive margin responses.

4.2 Identification

The validity of the research design to identify the labor market equilibrium effects of wage subsidies depends on two sets of assumptions. The first set relates to the structure of the labor market, namely having distinct labor markets and substitutable workers. The second set relates to the validity of the shift-share IV design when shocks are quasi-randomly assigned. I now discuss these assumptions and their validity given the French institutional context described in Section 2.

Assumption 1. *(Local labor markets are distinct).*

Defining local labor markets as closed units ensures that the labor market is in equilibrium at this cluster level (Hamermesh, 1996; Rothstein, 2010). This approach captures the relevant spillovers without contamination from labor market decisions in other areas.

First, Figure 2 presents two distributions illustrating mobility patterns across local labor markets. First, in panel (a), I plot the distribution of the percentage of individuals residing in the same local labor market between time t and $t + 3$, using the main analysis sample. Residential mobility is very limited, with a mean of 95% and a standard deviation of 3%. The first and third quartiles are 95% and 97%, respectively. This mobility pattern is similar to that observed for commuting zones, which are statistical divisions of France specifically designed for local labor market analysis. Table A.4 compares the distribution of the percentage of stayers across local labor markets over time, between local labor markets defined as départements in panel (a) and commuting zones in panel (b). The two distributions are almost identical.

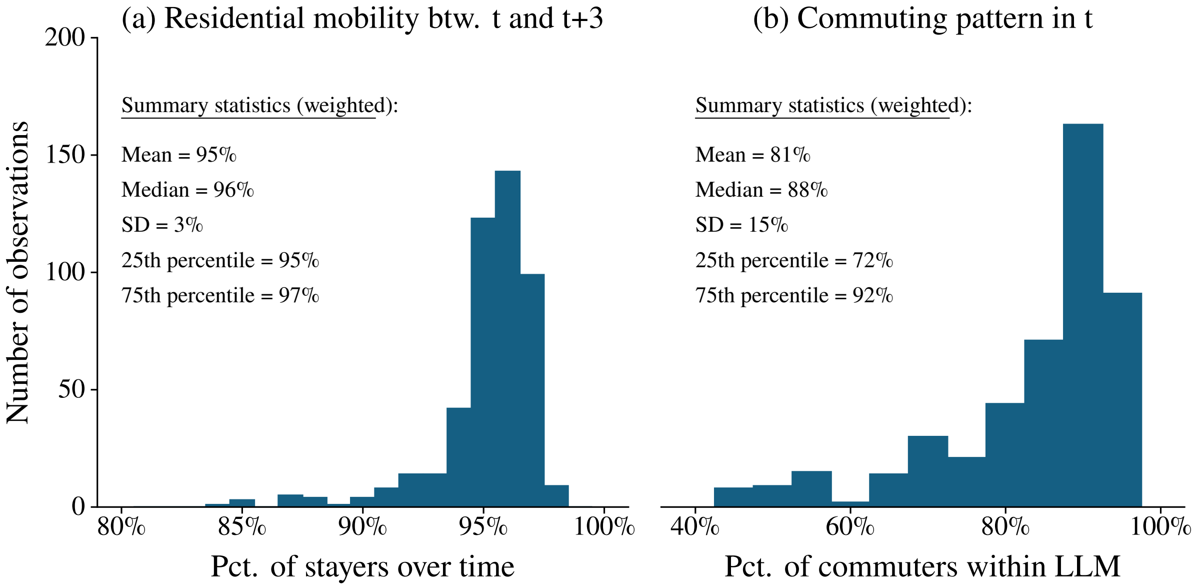
Second, panel (b) of Figure 2 uses census data to determine the percentage of individuals who work in the same local labor market where they live in a given year. Most individuals commute within their respective local labor markets, with a mean of 81% and a median of 88%. The first and third quartiles are 72% and 92%, respectively. Census estimates are likely conservative, as they include high-skilled and high-wage individuals who tend to be more mobile.

Overall, these findings suggest that local labor markets are effectively insulated, and the limited potential for spillovers across them does not pose a threat to the identification strategy. The results are quantitatively similar when using either definition of local labor markets–départements or commuting zones–confirming the validity of my primary local labor market definition.

Assumption 2. *(Socio-economic groups are substitutable in the labor market).*

The underlying mechanism behind this assumption is that wage subsidy shocks generate equilibrium effects in the labor market. Specifically, individuals' labor supply decisions in response to wage subsidy shocks spillover to other socioeconomic groups because they are substitutable in the labor market, even if imperfectly.

Figure 2: Local labor markets mobility patterns



Notes: The figure illustrates mobility patterns across local labor markets (LLMs). Each observation represents a unique combination of a local labor market and a time period. Panel (a) shows a histogram of the percentage of individuals remaining in the same local labor market between two time periods (t and $t + 3$), based on the main sample described in Section 2. Panel (b) displays a histogram of the percentage of commuters who live and work within the same local labor market in a given initial year t (2011–2015), using census data with demographic restrictions similar to those in the main sample. Summary statistics in both panels are weighted by each local labor market's share in the national observed population.

Numerous studies have found that workers are substitutable in the labor market, as summarized by the meta-study by Mercan et al. (2024). For example, Card and Lemieux (2001) find that the elasticity of substitution (ES) between high school and college graduates ranges from 1.1 to 1.6, with an ES between cohorts within each group between 4 and 5.9. Similarly, Borjas (2003) report an ES of 3.5 between workers of similar education but different experience levels. Autor et al. (2008) show that the ES between high school and college graduates is around 1.6. Additionally, Mercan et al. (2024) find an ES of approximately 1.3 between new hires and incumbent workers. Finally, Jäger and Heining (2022) find that new hires and incumbent workers are imperfect substitutes using data on worker deaths in Germany, with an ES between workers in different occupations of 20.

In summary, these studies strongly suggest that workers are imperfect substitutes in the labor market and are far from being complements. My research design does not rely on the assumption of perfect substitutability and allows for imperfect substitution in the labor market, as exemplified by the model with heterogeneous labor demand in Section 2.

Assumption 3. *(Conditional quasi-random shock assignment).*

$$\mathbb{E}[\tilde{g}_{n,t}^{1-MTR} | \bar{\epsilon}_{n,t}, \bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}] = \bar{\mathbf{\Lambda}}'_{n,t} \mu^{1-MTR} \quad \textit{and} \quad \mathbb{E}[\tilde{g}_{n,t}^{1-ATR} | \bar{\epsilon}_{n,t}, \bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}] = \bar{\mathbf{\Lambda}}'_{n,t} \mu^{1-ATR}, \forall (n,t).$$

This condition implies that each shock has the same expected value, given the shock-level unobservables $\bar{\epsilon}_{n,t}$, the average exposure $s_{n,t}$, and the shock-level observables $\bar{\mathbf{\Lambda}}_{n,t}$. Intuitively, it means that changes in wage subsidies should not have been strategically chosen based on change in labor market trends or in a way that is correlated with such changes.

This assumption naturally holds in my research design since the wage subsidy schedule is set at the national level and is not directly linked to local labor market characteristics. For individuals with similar household characteristics (such as household income, marital status, and the number of children), the amount of wage subsidies received remains the same across all local labor markets. Consequently, the magnitude of the shock (conditional on a set of controls, including shock-level fixed-effects) is unlikely to be correlated with unobservable labor market features that may influence outcomes.

To further test this assumption, I implement falsification tests following Borusyak et al. (2022). I regress potential confounders directly on the two instruments $z_{l,t}^{1\text{-}MTR}$ and $z_{l,t}^{1\text{-}ATR}$ (normalized to have unit variance), using the same set of controls as in the baseline regression and the equivalent shock-level approach for exposure-robust standard errors. Potential confounders are unobserved components that affect labor supply or demand and are correlated with tax shocks. I examine two sets of variables that serve as proxies for these confounders.

First, I consider start-of-period placebo variables that broadly reflect initial differences in productivity per worker across local labor markets. Using firm-level data, I calculate, for each local labor market in the initial year $t = 2011, \ldots, 2015$, the average value-added per worker (both gross and net of production taxes and subsidies), the average wage bill per worker, and the average financial revenue per worker.[24] All variables are in thousands of euros. If the tax shocks between t and $t + 3$ are as good as randomly assigned, they should not predict initial differences in these variables. Panel (a) of Table 3 shows that there is no correlation between these variables (in levels) and my two instruments.

Second, I conduct a "pre-trends" analysis by regressing lagged outcome variables on current shocks. Specifically, I regress the log-growth rates of labor earnings, hours worked, and wage rates from periods 2011–2013 and 2012–2014 on instruments for periods 2014–2016 and 2015–2017, respectively. I limit my analysis to two-year log-growth rates to include local labor market, socio-economic group, and period fixed-effects, as in my main design. This regression checks whether past outcomes are correlated with changes in wage subsidies generated by the reform. If Assumption 3 holds, the coefficients should not be statistically significant. Again, panel (b) of Table 3 shows that there is no correlation between these variables and my two instruments.

Assumption 4. *(Many uncorrelated shock clusters).*

[24] The first definition of gross value-added relates to production, while the second one–net of production taxes and subsidies–reflects the firm's revenue. The wage bill represents the firm's labor costs. Financial revenue comes from the company's financial investments and differs from income related to its regular operations.

Table 3: Balance tests, SSIV research design

	Net-of-tax rate		Net-of-participation-tax rate		
Balance variable	Coefficient	Standard Error	Coefficient	Standard Error	N
(a) Start-of-period placebo variables					
Gross value-added p.w.	0.654	(0.578)	-0.134	(0.277)	470
Net value-added p.w.	0.670	(0.526)	-0.261	(0.275)	470
Wage bill p.w.	-0.045	(0.252)	-0.085	(0.142)	470
Financial revenue p.w.	-0.204	(0.194)	-0.011	(0.104)	470
(b) Pre-trends: two-year log-growth rates					
Labor earnings	-0.002	(0.005)	0.000	(0.003)	188
Hours	-0.003	(0.004)	0.000	(0.002)	188
Wage rate	0.001	(0.002)	0.001	(0.001)	188

Notes: This table presents the results of falsification tests assessing the validity of the instruments $z_{l,t}^{1\text{-}MTR}$ and $z_{l,t}^{1\text{-}ATR}$. In panel (a), placebo variables (in levels) for the start-of-period year t are regressed on instruments defined between t and $t+3$. The five time periods are 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018. Net value-added is the gross value-added minus production taxes and subsidies. All balance variables are in thousands of euros. In panel (b), lagged outcome variables are regressed on current instruments. N represents the number of local labor market-period observations. Results are derived from equivalent shock-level regressions to ensure exposure-robust standard errors. All regressions include fixed effects for local labor markets, periods, and socio-economic groups, along with base-year controls (average hours worked and wage rates at the local labor market level). Standard errors are clustered at the socio-economic group level, and the instruments are normalized to have unit variance.

There exists a partition of shocks into clusters $c(n)$ such that:

$$
\begin{cases}
\mathbb{E}\left[\sum_c s_c^2\right] \rightarrow 0, \quad \textit{with } s_c = \sum_{\substack{(n,t):\\ c((n,t))=c}} s_{n,t} \\
\mathbb{C}ov(\tilde{g}_{(n,t)}^{1-MTR}, \tilde{g}_{(n,t)'}^{1-MTR} | \bar{\epsilon}_{n,t}, \bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}) = 0, \quad \forall ((n,t),(n,t)') \textit{ with } c((n,t)) \neq c((n,t)') \\
\mathbb{C}ov(\tilde{g}_{(n,t)}^{1-ATR}, \tilde{g}_{(n,t)'}^{1-ATR} | \bar{\epsilon}_{n,t}, \bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}) = 0, \quad \forall ((n,t),(n,t)') \textit{ with } c((n,t)) \neq c((n,t)').
\end{cases}
$$

As discussed in the estimation strategy, shocks are allowed to be clustered at the socio-economic group level. The first condition provides an intuitive measure of the effective sample size: shocks should not be concentrated in a small number of socio-economic groups. This is equivalent to saying that as the number of observations increases, the largest importance weight in the regression, denoted as s_c, becomes vanishingly small. The second part asserts that the shocks are mutually uncorrelated across clusters, given the unobservables, controls and $s_{n,t}$.

Panel (c) of Table 2 displays the inverse Herfindahl index, calculated as $1/\sum_{n,t} s_{n,t}^2$, which equals 243. It also displays the inverse Herfindal index across socio-economic groups, calculated as $1/\sum_n(\sum_t s_{n,t})^2$, which equals 49. Borusyak et al. (2022) demonstrate that shock-level estimations are robust even with an effective sample size as low as 20. Similarly, the largest share in my sample is small, below 1%.

Assumption 5. *(Relevance condition).*

$$\mathbb{E}[\bar{x}_{n,t}^{1-MTR}\tilde{g}_{n,t}^{1-MTR}|\bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}] \neq 0 \quad \textit{and} \quad \mathbb{E}[\bar{x}_{n,t}^{1-ATR}\tilde{g}_{n,t}^{1-ATR}|\bar{\mathbf{\Lambda}}_{n,t}, s_{n,t}] \neq 0.$$

Finally, the instruments must have sufficient statistical power, which can be verified by examining the first-stage F-statistic. More generally, $\tilde{g}_{n,t}^{1-MTR}$ and $\tilde{g}_{n,t}^{1-ATR}$–and by extension $z_{l,t}^{1-MTR}$ and $z_{l,t}^{1-ATR}$–qualify as strong instruments since they rely on individual characteristics from the initial period to predict the changes in shocks that would have occurred had individuals not changed their behavior.

Figure 3 illustrates the correlation between the instruments $\tilde{g}_{n,t}^{1-MTR}$ and $\tilde{g}_{n,t}^{1-ATR}$ and the equivalent observed exposure measures at the shock level, $\bar{x}_{n,t}^{1-MTR}$ and $\bar{x}_{n,t}^{1-ATR}$. Panel (a) displays the relationship for the net-of-tax rate, while panel (b) shows the relationship for the net-of-participation-tax rate. Each regression is based on the baseline specification, controlling for local labor market, period, and socio-economic fixed-effects, as well as base-year controls. Both exposure measures display a sharp positive relationship with their respective instruments, suggesting strong first-stages.

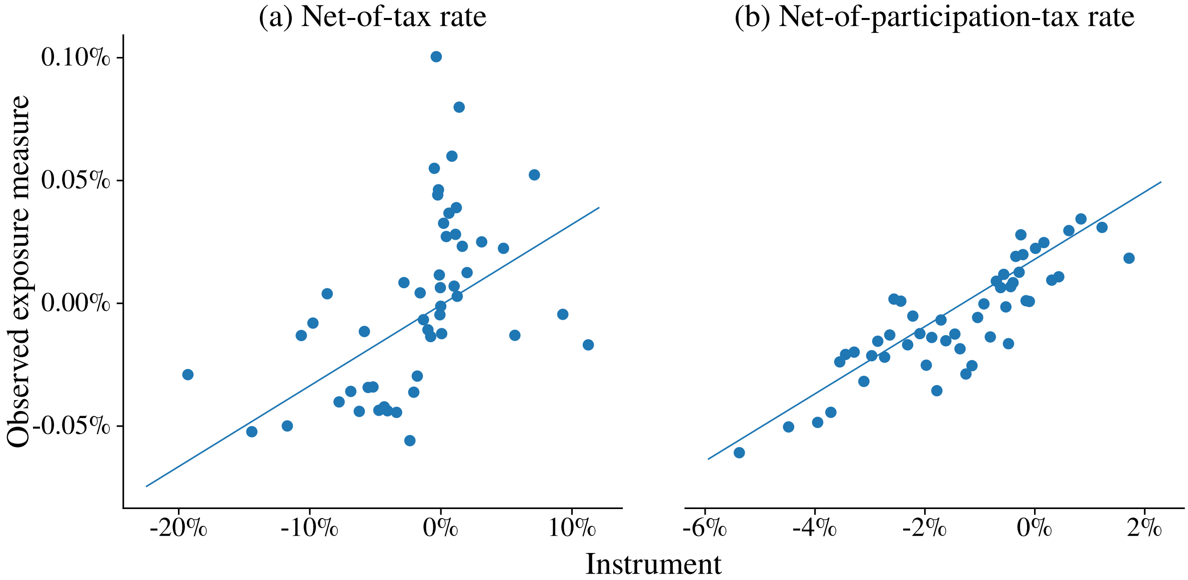
Heterogeneous treatment effects and negative weights. In linear fixed-effects regressions, a potential issue that can arise is the sign-reversal of the estimand. This occurs due to the negative weights assigned to certain groups when there are heterogeneous treatment effects (for an overview, see De Chaisemartin and d'Haultfoeuille (2023)). Heterogeneous local labor market or socio-economic group effects are plausible in my context. Borusyak et al. (2022) and Borusyak and Hull (2024) show that this concern is not applicable in "design-based" specifications, as they capture a convex average of treatment effects. More precisely, in such specifications, the weights applied to heterogeneous treatment effects are determined by "ex-ante weights", which are the expectations of treatment weights ("ex-post weights") over the treatment assignment. Shift-share instruments, and consequently my research design, rely on a model of instrument assignment, which fall under this interpretation.[25]

5 Results

This section presents the results from the shift-share IV research design outlined in Section 4. My outcomes of interest are three-year log-growth rates at the local labor market level, indexed by initial year t, in the total number of hours worked $g_{l,t}^{H} = \ln(H_{l,t+3}) - \ln(H_{l,t})$; the average hourly

[25]In particular, it relies on both assumptions of first-stage monotonicity and mean-independence.

Figure 3: First-stage estimations, SSIV research design



Notes: The figure illustrates the first-stage relationship underlying the shift-share IV research design for the baseline specification. Specifically, it plots the correlation between the observed tax shocks and the corresponding instruments using the equivalent shock-level IV regression. Each regression includes local labor market, period, and socio-economic group fixed effects, as well as base-year controls and the two instruments. Panel (a) shows the correlation for the net-of-tax rate, while panel (b) shows the correlation for the net-of-participation-tax rate. For example, in panel (a), the x-axis represents $\tilde{g}_{n,t}^{1-MTR}$ and the y-axis represents $\bar{x}_{n,t}^{1-MTR}$. Observations are weighted by the average socio-economic group exposure share $s_{n,t}$, and each dot represents 1% of the data.

wage $g_{l,t}^{w} = \ln(w_{l,t+3}) - \ln(w_{l,t})$; and the total labor earnings $g_{l,t}^{E} = \ln(w_{l,t+3}H_{l,t+3}) - \ln(w_{l,t}H_{l,t})$. I report estimates from the equivalent shock-level IV regression defined in equation (9), weighted by the average exposure of the socio-economic group $s_{n,t}$.

5.1 Baseline SSIV results

Equilibrium effects of wage subsidies. Table 4 presents the local labor market equilibrium effects estimated from the shift-share IV research design, based on my preferred specification. This specification includes fixed effects for local labor markets, periods, and socio-economic groups, as well as base-year controls such as the average number of hours worked and wage rates at the local labor market level in the initial year t. I report standard errors clustered at the socio-economic group level.

First, the shift-share IV statistics confirm that the instruments are strong and that the research design is valid. The first-stage F-statistics are 58 for the net-of-tax rates and 238 for the net-of-participation-tax rates, indicating strong shift-share instruments.

Second, there are significant labor market equilibrium responses. Column (1) reports the employment effects. The point estimate for the elasticity with respect to the net-of-tax rate is 0.007 (SE = 0.100), while for the net-of-participation-tax rate it is 0.270 (SE = 0.093). Only the second coefficient is statistically significant. In column (2), similar elasticities for the hourly wage rate are presented. The point estimate is 0.059 (SE = 0.086) for the net-of-tax rate and -0.309 (SE = 0.067) for the net-of-participation-tax rate. Again, only the second coefficient is statistically significant. This means that a uniform increase of 10% in the net-of-participation-tax rate is associated with a 2.70% increase in the number of hours worked and a 3.09% decrease in the average hourly wage, compared to the situation without any change in wage subsidies.

Third, column (3) reports the results for labor earnings, which combine the wage and employment effects. The point estimates are 0.067 (SE = 0.160) for the net-of-tax rate and -0.038 (SE = 0.142) for the net-of-participation-tax rate, and both are not statistically significant. The wage effect approximately offsets the employment effect, indicating that, on average, labor earnings (before redistribution) are not affected by an increase in wage subsidies. It implies that the labor demand is not completely elastic. Keeping the simple conceptual framework from Section 2.2 in mind, the total number of hours worked in a labor market inversely relates to the labor demand elasticity. Intuitively, as labor demand becomes more rigid, employers do not significantly adjust their employment. Conversely, the wage rate becomes highly responsive to increases in labor supply.

However, it is important to note that the null effects on labor earnings should not be interpreted as stagnation in absolute terms. In France, labor earnings are generally growing over time. The fixed effects and base-year controls absorb specific labor supply and labor demand trends, as well as period-specific shocks. Therefore, an increase in the net-of-tax rate or net-of-participation-tax rate leads to a decrease in prospective wages. In other words, without wage subsidies, labor earnings and wage rates would have experienced higher growth rates.

Economic incidence. The wage effect from Table 4 suggests an average pass-through of wage subsidies to wages of 31%. This result is quantitatively consistent with the limited literature on the economic incidence of wage subsidies.

First, Leigh (2010) finds that a 10% increase in the EITC decreases the hourly wage rate by 5% for high school dropouts, using variation in U.S. state-level EITC programs. His analysis uses wage and employment levels, while mine focuses on log-growth rates. Nichols and Rothstein (2015) show that these estimates imply a very high pass-through of wage subsidies to wages, averaging 500%. In contrast, my pass-through rate is more reasonable and compatible with standard incidence models.

Second, the magnitude of my wage and employment effects is consistent with Rothstein (2010), who conducted a calibration using a competitive labor market model in the United States. His analysis primarily focuses on the labor market for women, whereas my paper includes all low-wage earners. Nevertheless, my results are similar to his for a reasonable set of micro elasticities. For example, Rothstein (2010) finds that under the assumption of perfect competition in the labor market and with a labor demand elasticity of -1, a labor supply participation elasticity of 0.5, and a compensated elasticity of labor supply of 0, a one-percentage-point increase in the net-of-participation-tax rate leads to a 33% increase in labor supply and a 33% decrease in the wage rate.[26]

Finally, Zurla (2024) identifies a pass-through rate of 30% in the context of an Italian EITC program. However, our institutional contexts—and therefore interpretations of the policy—differ for two reasons. First, Zurla (2024) leverages variations in program exposure at the firm level, while my analysis focuses on responses at the level of local labor markets. Second, the distribution of the Italian wage subsidy is administered by the firm, whereas in the French context it is directly distributed to workers and is therefore less salient to the firm.[27]

5.2 Discussion and Robustness

Local labor markets definition. I test the robustness to an alternative local labor market definition using commuting zones, which by design satisfy the assumption of distinct and closed labor markets. Table A.5 reports results using the baseline specification. These results are consistent with the main findings in Table 4. First, there are no significant responses with respect to changes in the net-of-tax rates for the number of hours worked, wage rate, and labor earnings. Second, there are significant wage and employment responses with respect to changes in the net-of-participation-tax rates, with an employment elasticity equal to 0.300 (SE = 0.112) and a wage rate elasticity equal to -0.252 (SE = 0.068). Finally, the wage and employment effects offset each other, so labor earnings are not affected by changes in wage subsidies. These estimates are not statistically different from the point estimates using the main local labor market definition.

Different period lengths. A potential concern is that individuals may gradually adapt to the reform, meaning that my results might underestimate the wage and employment effects in the long run. This is especially relevant in contexts characterized by salience effects, information gaps regarding wage subsidy programs, or infrequent wage renegotiation. While my baseline analysis mitigates these concerns by examining three-year log-growth rates, I further address the issue by also analyzing two-year log-growth rates. Assuming that agents fully adjust within two years after the reform, the magnitude of the coefficients should be similar for periods of two and three years. Table A.6 presents the results for these two year horizons. Notably, the wage effect with respect to the net-of-participation-tax rate after three years (column (3)) is almost identical to that after two years (column (4)), being -0.309 (SE = 0.067) and -0.304 (SE = 0.058), respectively. This suggests that the incidence stabilizes after two years and is consistent

[26]It is also consistent with the findings of Kroft et al. (2020), who exploit variation in tax liabilities from EITC reforms between 1994 and 2010 to estimate macro-level participation and employment elasticities of 0.48 and 0.42, respectively, at the U.S. state level. However, they do not estimate the effects on hours worked or average hourly wage rates.

[27]Azmat (2019) finds that salience is important for understanding the incidence of the Working Families' Tax Credit in the UK.

Table 4: Shift-share IV estimates

	Three-year log-growth rates		
	Hours	Wage rate	Labor earnings
	(1)	(2)	(3)
Equivalent shock-level exposure measures			
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	0.007	0.059	0.067
	(0.100)	(0.086)	(0.160)
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.270***	-0.309***	-0.038
	(0.093)	(0.067)	(0.142)
Controls			
Socio-economic group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Local labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓
SSIV statistics			
No. of socio-economic groups-periods	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	57.9	57.9	57.9
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	237.8	237.8	237.8

Notes: This table reports coefficients from shift-share IV regressions for the three-year change in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (column (1)), the hourly wage rate (column (2)), and total labor earnings (column (3)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

with Kleven and Schultz (2014), which shows that three-year differences capture behavioral responses to Danish tax shocks.

Alternative specifications. Table A.7 further assesses the robustness of my results using alternative specifications. First, I introduce less stringent sets of fixed effects by splitting the socio-economic group fixed effects into three distinct categories: household income bin fixed effects, a binary variable for marital status, and a binary variable for having children. Second, I augment my baseline regression with additional base-year controls, including the proportion of individuals close to the minimum wage, those working full-year, and those working full-time. Finally, I employ the same shift-share IV approach as in the baseline analysis to regress the set of outcomes separately on each tax measure. Overall, the coefficients remain quantitatively similar to those in my baseline specification.

Alternative samples. Table A.8 tests the sensitivity of my results to the sample restriction that pre-tax hourly wages are below €14 per hour in the initial year t. Specifically, I examine two alternative samples by increasing this threshold to €14.50 and €15 per hour, respectively.[28] The results remain quantitatively similar to those from the baseline sample. For example, the wage effect with respect to the net-of-participation-tax rate is -0.222 (SE = 0.058) for the €14.50 threshold and -0.210 (SE = 0.057) for the €15 threshold.

Gross labor earnings and wages. My baseline analysis uses taxable labor earnings, which exclude employer payroll taxes and part of employee payroll taxes. Between 2013 and 2016, several reductions in employer payroll taxes were implemented, primarily targeting workers earning less than 3.5 times the national minimum wage.

Conceptually, there are two reasons why my results should not be driven by these reforms. First, in the context of the initial set of payroll tax reductions in 2013, Bozio et al. (2024) find a limited pass-through effect of employer payroll taxes to workers due to the absence of a tax-benefit linkage. Specifically, net labor earnings–which closely align with my labor earnings definition–remain unaffected. Second, the non-linear nature of the tax and benefit schedule at the individual level ensures that my source of variation differs from that of the payroll tax reductions, especially when including period, local labor market, and socio-economic group fixed effects.[29]

To directly test this assumption, I compute gross labor earnings and gross wage rates at the individual level, as well as net-of-tax rates and net-of-participation-tax rates that account for payroll taxes. I use OpenFisca, which allows me to calculate these metrics based on taxable labor earnings and employment characteristics. Then, I follow the methodology from Section 3 to construct my outcome and exposure measures at the local labor market level, as well as shocks at the socio-economic group level. This is not my preferred specification because computing these metrics from the available data is inherently difficult due to the complexity of the French payroll tax system. Therefore, the computed values are only approximations of the true values.[30]

[28]The sixth, seventh, and eighth deciles of net labor earnings are €12.54, €14.21, and €16.94, respectively (see Section 3). Note that INSEE uses net labor earnings after social contributions, which are slightly lower than taxable labor earnings because the latter include some social contributions.

[29]Table A.9 reports shift-share OLS regressions of the exposure measures (or simulated tax shocks) that include payroll taxes on their baseline counterparts, separately for the net-of-tax rate and the net-of-participation-tax rate. In all specifications, the baseline measures strongly predict the versions incorporating payroll taxes. In particular, when controlling for socio-economic group and period fixed effects, the coefficients on the simulated tax shocks are essentially one, with an adjusted R^2 near one. This indicates that potential changes in payroll taxes do not confound my instruments.

[30]First, the payroll tax system is structured in a way that makes it difficult to directly compute the actual payroll taxes paid, leading to noisy approximations. Second, I need to make assumptions about certain individual characteristics–for example, that individuals are employed in the private sector and are not executives. Nevertheless, this approach is overall representative of the payroll system in France.

Table A.10 presents the results using these alternative measures. The coefficients are similar to those obtained using the baseline measures, consistent with theoretical predictions. For example, the employment effect and the wage effect with respect to the net-of-participation-tax rate are 0.270 (SE = 0.089) and -0.287 (SE = 0.055), respectively.

6 Mechanisms

To understand the drivers behind the wage and employment effects at the local labor market level, I examine the various channels of response at the micro level. Specifically, I analyze wage and labor supply responses to wage subsidies at a more disaggregated level than in Section 5–namely, at the socio-economic group level within local labor markets. First, I present the main prediction from the incidence framework regarding these responses. Second, I develop an empirical strategy to test this prediction.

6.1 Conceptual Framework

The model presented in Section 2.2 illustrates how wage subsidies affect labor supply both directly and indirectly. For each socio-economic group n in local labor market l, the total change in labor supply combines two factors: the decision to participate in the labor market and to be employed (extensive margin) and the number of hours worked by those who are employed (intensive margin). This means the growth rate of total hours worked ($g^H_{l,n}$) is the sum of the growth rate in the employment rate ($g^P_{l,n}$) and the growth rate in hours worked conditional on employment ($g^h_{l,n}$). The total change in labor supply is thus given by:

$$g^H_{l,n} = \underbrace{\beta^H g_n^{1-\text{MTR}} + \gamma^H g_n^{1-\text{ATR}}}_{\text{Direct effect}} + \underbrace{\sigma^H g_l^w}_{\text{Indirect effect}} .$$

The direct effect captures the expected labor supply responses to direct tax shocks at the micro level. An increase in the net-of-participation-tax rate and the net-of-tax rate incentivizes individuals to participate more in the labor market and to work additional hours. This represents a positive shift in the labor supply, quantified by labor supply elasticity at the intensive margin β^H and the employment elasticity γ^H.

The indirect effect relates to how wages adjust to an increase in labor supply at the local labor market level l. For a given labor demand, an increase in labor supply leads to a decrease in the prospective wage rate. Specifically, the wage effect depends on the labor market's exposure to changes in the net-of-tax rate and net-of-average-tax rate, expressed as $g^w_l = \alpha^w + \beta^w x_l^{1-\text{MTR}} + \gamma^w x_l^{1-\text{ATR}}$, with $\beta^w \leq 0$ and $\gamma^w \leq 0$. The magnitude of the indirect effect is captured by the spillover coefficient σ^H.

This conceptual framework can be extended to encompass multiple periods and to incorporate heterogeneity in wages across socio-economic groups within local labor markets. In a nutshell, labor supply for socio-economic group n in local labor market l in period t is always a function of direct micro-level responses to the group's net-of-tax rate and net-of-participation-tax rate, as well as the (indirect) wage effect in local labor market l during period t. Consequently, the incidence framework has the following main prediction.

Prediction 1. *At the group-by-market-by-period level, labor supply responds to direct wage subsidy shocks, whereas wages are expected to remain unaffected.*

When comparing socio-economic groups within the same market and period, the indirect effect of wage subsidies–which occurs at the local labor market level–cancels out. Therefore, an estimation strategy that relies solely on comparisons across socio-economic groups within the same local labor market and time period will capture only the direct effect of wage subsidies. Using this empirical framework, a placebo test involves checking whether the growth rate of the hourly wage at the group-by-market-by-period level, $g^{w}_{l,n,t}$, responds to the net-of-tax rate and net-of-average-tax rate. Since we expect the wage rate to be determined solely by market equilibrium adjustments, there should be no direct effect, and the coefficients should be equal to zero.

Corollary 1. *Wages are affected through equilibrium responses at the market level (spillover effect).*

If Prediction 1 is correct, the group-by-market-by-period log-growth rate of hourly wages, $g^{w}_{l,n,t}$, should show no response to direct tax shocks. By contrast, the average wage rate in the local labor market should respond to the market's overall exposure to changes in net-of-tax and net-of-participation-tax rates. As shown by the shift-share IV results in Section 5, wages at the local labor market level decline in response to an increase in wage subsidies. Thus, if Prediction 1 holds, wages can only be affected through equilibrium channels operating at the local labor market level, rather than via direct tax shocks at the group level.

6.2 Sample and Variables

Sample. I use definitions for local labor markets, socio-economic groups, and time periods similar to those in Section 3, following the same sample restrictions as in my baseline sample. Specifically, local labor markets are defined as départements, and I restrict the sample to individuals whose pre-tax hourly wage rate is below €14 per hour in the initial year. The outcomes of interest are measured at the socio-economic group, local labor market, and period level, which I index by (l, n, t). Due to this level of disaggregation, I limit the analysis to cells containing more than ten individuals. I compute three-year growth rates ($h = 3$), with the initial year t ranging from 2011 to 2015, where 2015 is the last year of earnings before the reform. Therefore, the five periods are 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018.

Outcomes. For each cell (l, n, t), I follow the procedure outlined in Section 2 to compute the total number of hours worked $H_{l,n,t}$, the employment rate $P_{l,n,t}$, the average wage rate $w_{l,n,t}$, and total labor earnings $E_{l,n,t}$.[31]

I then define a set of log-growth rates for each of these labor market outcomes. Consistent with the local labor market analysis, individuals' residence and socio-economic group in the initial period are used to define their respective cells, thereby reducing potential measurement bias from composition effects. These log-growth rates are calculated between periods t and $t + h$, with indexing by the initial year t for clarity and with $h = 3$. All outcomes are winsorized at the 1th and 99th percentiles each period.

First, I define the log-growth rates of the employment rate, average wage rate, and total labor earnings as follows: $g^P_{l,n,t} = \ln(P_{l,n,t+h}) - \ln(P_{l,n,t})$, $g^w_{l,n,t} = \ln(w_{l,n,t+h}) - \ln(w_{l,n,t})$, $g^E_{l,n,t} = \ln(E_{l,n,t+h}) - \ln(E_{l,n,t})$.

Second, I define the change in the number of hours worked as $g^H_{l,n,t} = g^E_{l,n,t} - g^w_{l,n,t}$. By defining it this way, the measure of hours worked $g^H_{l,n,t}$ captures responses at both the intensive and extensive margins. This distinction helps clarify the extent to which changes in hours worked are driven by variations in employment versus adjustments in hours among those already employed.

Finally, Table A.11 summarizes the distribution of the labor market outcomes and key start-of-period labor market characteristics at the cell level, for the period from 2011 to 2018. All variables are weighted by the number of observations in each cell in the initial year $t = 2011, \dots, 2015$.

Tax shocks and exposure measures. I directly use tax shocks constructed from the full sample (see Section 2) and defined at the socio-economic group and period level (n, t). These include the net-of-tax rates $g^{1-MTR}_{n,t}$, net-of-participation-tax rates $g^{1-ATR}_{n,t}$, and their respective instruments $\tilde{g}^{1-MTR}_{n,t}$ and $\tilde{g}^{1-ATR}_{n,t}$. As a robustness check, I also define these tax shocks at the socio-economic group, local labor market, and period level (l, n, t). The results remain quantitatively similar, supporting the assumption that treatment intensity varies by socio-economic group but not across local labor markets.

Finally, I use exposure measures constructed from the full sample, as detailed in Section 2. These measures, defined at the local labor market and period level (l, t), include the exposure measure with respect to the net-of-tax rates $x^{1-MTR}_{l,t}$ and net-of-participation-tax rates $x^{1-ATR}_{l,t}$, along with their respective instruments $z^{1-MTR}_{l,t}$ and $z^{1-ATR}_{l,t}$.

[31]The employment rate is defined as the ratio of individuals earnings zero labor earnings over the total number of individuals in a cell.

6.3 Empirical Strategy

This section assesses the direct effect of wage subsidies on outcomes, as outlined by Prediction 1. I develop an IV research design that relies exclusively on within-local-labor-market and within-period comparisons across socio-economic groups. Intuitively, this empirical strategy eliminates the indirect effect of wage subsidies arising from labor market equilibrium, allowing me to isolate the direct effect of wage subsidies on labor market outcomes.

Specification. I denote the outcome at the socio-economic group, local labor market, and period level by $y_{l,n,t}$. The primary outcomes of interest are the three-year log-growth rates in the employment rate, number of hours worked, average wage rate, and total labor earnings. The coefficients of interest, β and γ, are estimated using the following specification:

$$y_{l,n,t} = \lambda_{l,t} + \beta g_{n,t}^{1-MTR} + \gamma g_{n,t}^{1-ATR} + \mathbf{\Lambda}'_{l,n,t}\boldsymbol{\theta} + \epsilon_{l,n,t}, \tag{10}$$

where $\lambda_{l,t}$ represents a market-by-period fixed effect, $\mathbf{\Lambda}_{l,n,t}$ is a set of control variables, $g_{n,t}^{1-MTR}$ and $g_{n,t}^{1-ATR}$ represent the net-of-tax rates and net-of-participation-tax rates, respectively, and $\epsilon_{l,n,t}$ is an error term. Each regression is weighted by the number of individuals within each cell and standard errors are clustered at the group-by-market level. When estimating equation (10), I exclude singleton observations that cannot be identified given the fixed effects and controls.[32]

Identification. This specification relies on within-local-labor-market and within-year variation in tax shocks to identify β and γ. Specifically, the market-by-period fixed effect $\lambda_{l,t}$ absorbs the indirect (equilibrium) effects of wage subsidies that are embedded in the broader exposure measures, $x_{l,t}^{1-MTR}$ and $x_{l,t}^{1-ATR}$. Consequently, this empirical strategy isolates and captures only the direct effects of wage subsidies on the specified outcomes, netting out any equilibrium adjustments occurring at the market level.

To address endogeneity concerns stemming from potential reverse causality between the outcomes and tax shocks, I instrument the tax shocks $g_{n,t}^{1-MTR}$ and $g_{n,t}^{1-ATR}$ with their simulated counterparts, $\tilde{g}_{n,t}^{1-MTR}$ and $\tilde{g}_{n,t}^{1-ATR}$, using two-stage least squares (2SLS) regressions. A substantial body of literature on simulated instruments supports that they generally meet the traditional instrumental variable assumptions, including relevance, monotonicity, and the exclusion restriction (e.g., Auten & Carroll, 1999; Moffitt & Wilhelm, 2000; Gruber & Saez, 2002; Kopczuk, 2005; Weber, 2014). First-stages are strong, as indicated by the F-stats > 20,000.

This specification also helps detect potential biases from selection-on-observables and compositional effects. In particular, a regression using the wage rate as the outcome should yield coefficients β and γ equal to zero. If it does not, there must be a systematic correlation between direct tax changes and wage changes. For example, systematic differences in the wages of new

[32]In the baseline specification, this reduces the number of observations from 21,122 to 20,423.

entrants versus incumbent workers within a socio-economic group could introduce measurement issues due to compositional effects, thereby biasing the results.

Controls. My preferred specification includes market-by-period fixed effects, market-by-group fixed effects, and base-year controls at the market-by-group-by-period level–specifically, the average number of hours worked and wage rates among individuals in each cell (l, n, t). I also control for heterogeneous growth rate along the household income distribution (e.g., Gruber & Saez, 2002; Kopczuk, 2005; Kleven & Schultz, 2014; Weber, 2014). For each base year t and separately by marital status (single versus couple), I construct a binary indicator set to one if the individual's household income exceeds the median.[33] Finally, to capture any period-specific and marital status effects, I interact this binary indicator with period and marital status fixed effects.

6.4 Micro Responses to Wage Subsidies

Baseline results. Columns (1) to (4) of Table 5 present the baseline IV estimates for three-year log-growth rates of the average wage rate, the employment rate, the number of hours worked, and labor earnings, respectively. Robustness checks under alternative specifications appear in Table A.12, and additional results using alternative instruments at the group-by-market-by-period level are reported in Table A.13.

First, I find that direct tax shocks have no significant effect on wages. The elasticity of the average wage rate is -0.011 (SE = 0.011) with respect to the net-of-tax rate and 0.021 (SE = 0.031) with respect to the net-of-participation-tax rate. This result–robust to alternative specifications and alternative instruments–is consistent with the conceptual framework in Section 6.1, indicating that wages respond only through local labor market equilibrium effects. It also rules out selection-on-observables: if systematic differences existed between the wages of new entrants and incumbent workers, one would expect a correlation between wage changes and direct tax shocks. The absence of a direct wage response suggests that such compositional biases are not driving the findings.

Second, direct tax shocks have a significant effect on individuals' employment. The employment elasticity with respect to the net-of-participation-tax rate is 0.159 (SE = 0.051), whereas the elasticity with respect to the net-of-tax rate is 0.007 (SE = 0.024) and not statistically significant. This pattern, which holds across various specifications and instruments, suggests that extensive-margin responses are a key channel for labor supply adjustments at the individual level.

The employment elasticity with respect to the net-of-participation-tax rate is on the lower

[33]More specifically, I use the bins of the equalized household income measure described in Section 3.2 to compute the median. Because the measure of household income is scaled by the number of adults in the household, I compute the median separately for single individuals and couples, and by year. The median is calculated by weighting each cell by its number of individuals.

Table 5: Micro responses to direct tax shocks

	Three-year log-growth rates			
	Wage rate (1)	Employment (2)	Hours (3)	Labor earnings (4)
Tax shocks				
Net-of-tax rates, g_{nt}^{1-MTR}	-0.011	-0.007	0.045*	0.035
	(0.011)	(0.017)	(0.024)	(0.024)
Net-of-participation-tax rates, g_{nt}^{1-ATR}	-0.021	0.159***	0.314***	0.298***
	(0.031)	(0.051)	(0.071)	(0.069)
Controls				
HH income group-Couple-Period F.E	✓	✓	✓	✓
LLM-SE group F.E	✓	✓	✓	✓
LLM-Period F.E	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓
IV statistics				
No. of observations	20,423	20,423	20,423	20,423
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	20,439.0	20,439.0	20,439.0	20,439.0
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	68,297.3	68,297.3	68,297.3	68,297.3

Notes: This table reports coefficients from IV regressions for the three-year change in the log of labor market outcomes on direct tax shocks. Labor market outcomes are defined by cells, each representing a combination of socio-economic group, local labor market, and period. Direct tax shocks are defined at the socio-economic group and period level. Each regression is weighted by the number of observations within each cell in the initial period. The direct tax shocks for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the hourly wage rate in column (1), the employment rate in column (2), the number of hours worked in column (3), and total labor earnings in column (5). Base-year controls include average hours worked and wage rates at the cell level in the initial year t. Standard errors are clustered at the socio-economic group-department level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

end of those reported in the meta-analysis by Chetty, Guren, et al. (2013), which range from 0.13 to 0.43. Much of the EITC-related studies focus on specific populations, particularly single women with or without children. A notable exception is Kroft et al. (2020), who exploit variation in tax liabilities stemming from EITC reforms spanning 1994–2010 and estimate an employment elasticity of 0.6. Differences in the institutional setting and sample selection likely explain part of the gap.[34] I explore this point further in the heterogeneity analysis below. By contrast, my estimate aligns more closely with Bastani et al. (2021), who find an average employment elasticity of 0.13 using comprehensive Swedish administrative data and a tax-and-transfer reform in 1997. Their setting is similar to mine, as both contexts feature already high

[34]Kroft et al. (2020) restrict their analysis to individuals with less than a bachelor's degree, while I do not have an educational restriction in my context.

employment rates among both men and women.

Finally, direct tax shocks significantly affect total labor supply. The elasticity of hours worked with respect to the net-of-participation-tax rate is 0.314 (SE = 0.071), whereas the elasticity with respect to the net-of-tax rate is 0.045 (SE = 0.024) and not significant at the 5% level. Elasticities for labor earnings are comparable, consistent with the notion that the identification strategy captures labor supply responses rather than a wage effect.[35] Overall, because hours and employment respond only to the net-of-participation-tax rate, the evidence implies that labor supply changes at the micro level predominantly reflect extensive margin adjustments.

Heterogeneity analysis. Different segments of the population may respond differently to changes in net-of-participation-tax and net-of-tax rates. For instance, socio-economic groups with many full-year workers are less likely to adjust at the extensive margin and should therefore exhibit only minimal responsiveness.

To explore these differences, I examine various socio-economic characteristics measured at the group n, local labor market l, and base year t level. Specifically, for each cell (l, n, t), I use the proportion of full-year workers, the proportion of men, the proportion of individuals earning near the minimum wage, household income per adult (separately by marital status), and the average labor earnings. For each base year t, I define binary indicators indicating whether the socio-economic group lies above or below the median of each variable.[36]

Groups with fewer full-year workers, a higher share of individuals near the minimum wage, and lower household income per adult or lower average labor earnings are expected to exhibit stronger labor supply responses for two main reasons. First, wage subsidies primarily target these groups. Second, these individuals tend to be less firmly attached to the labor market and thus more prone to adjusting on the extensive margin. However, I anticipate no significant direct wage effect for any subgroup, consistent with the interpretation that the hourly wage rate is only affected through equilibrium responses at the local labor market level and that selection-on-observables does not drive the observed wage response.

Figure 4 reports the IV results for these subgroups, distinguishing between the net-of-participation-tax rate and the net-of-tax rate. Panel (a) shows estimates for the wage rate, panel (b) for the employment rate, panel (c) for total hours worked, and panel (d) for total labor earnings.

First, direct tax shocks have no significant effect on wages for all subgroups. The estimated coefficients for the net-of-participation-tax rate and the net-of-tax rate are not statistically

[35]When I do not control for heterogeneous trends (see Table A.12), the coefficients for hours and earnings move closer to those for employment, suggesting differences in the number of hours worked often determined by employers once individuals choose to work.

[36]All medians are computed by weighting each cell by its population size. For household income per adult, I follow the strategy described in the IV framework, using bins of equalized household income and calculating medians separately by marital status and year.

different from zero at the 5% level. This pattern confirms that the wage effect observed at the local labor market is neither driven by direct tax shocks nor by compositional changes across and within subgroups.

Second, the net-of-participation-tax rate has a substantial effect on labor supply among subgroups that are expected to strongly respond to wage subsidies. For instance, groups with fewer full-year workers, a higher share of men, a higher share of individuals at or near the minimum wage, and lower household income per adult or average labor earnings show employment elasticities between 0.3 and 0.4, total labor supply (hours) elasticities between 0.42 and 0.66, and labor earnings elasticities between 0.35 and 0.59. In contrast, other subgroups have substantially lower elasticities, often not statistically significant at the 5% level.[37]

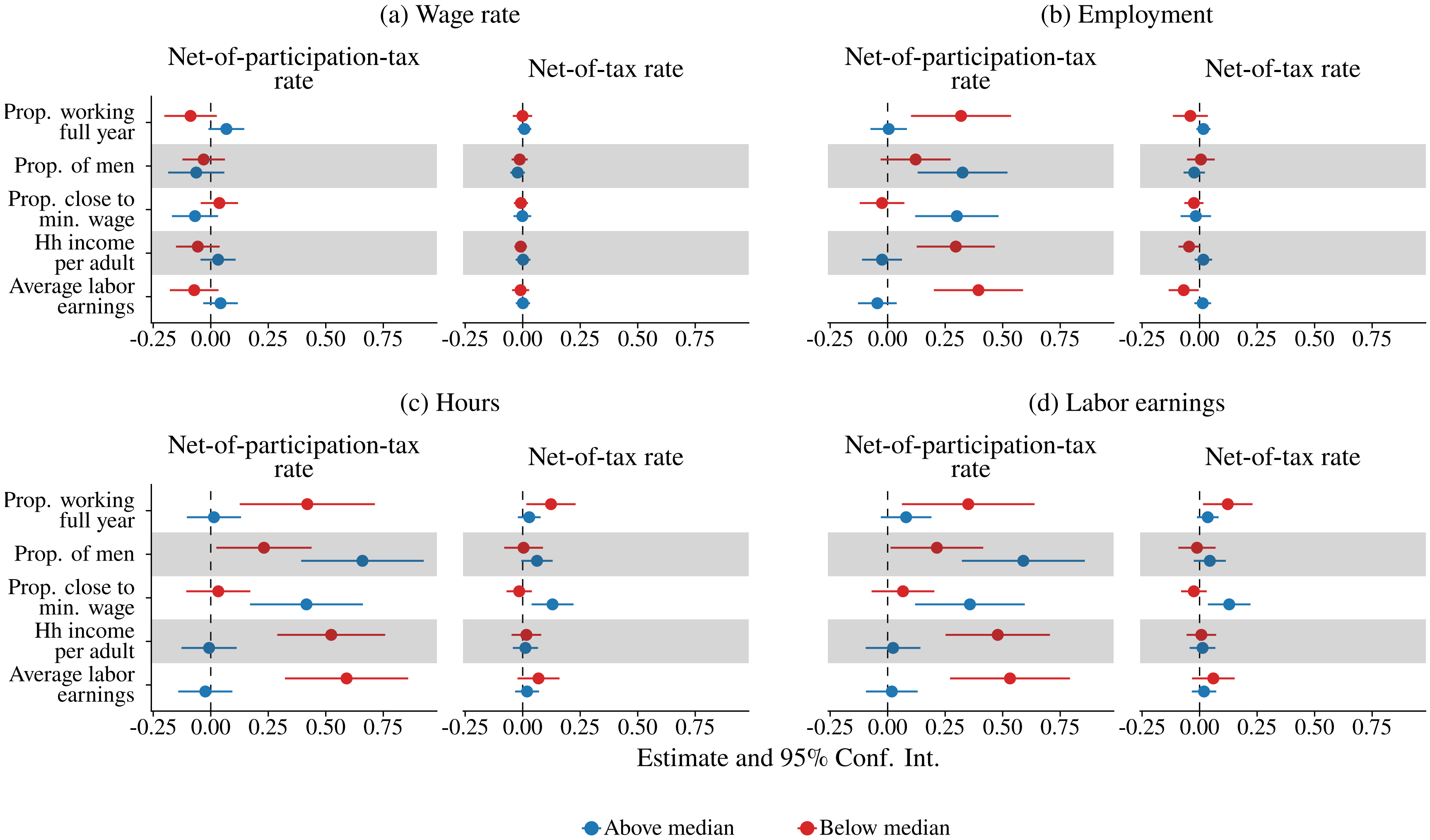
Finally, for all subgroups, there is little to no response in employment, hours, and labor earnings with respect to the net-of-tax rate. This finding reinforces the conclusion that the extensive margin is the primary channel through which labor supply responds to wage subsidies.

Discussion. Taken together, these findings support Prediction 1: in a given local labor market, socio-economic groups respond to direct tax shocks by adjusting labor force participation and employment–the primary goals of wage subsidies–while wages show no significant direct response. They also confirm Corollary 1: the wage effects of wage subsidies arise through equilibrium adjustments in the labor market.

It is helpful to connect these micro-level findings to the shift-share IV design in Section 4. Both approaches show that labor supply responds only to net-of-participation-tax rates. At the micro level, we detect heterogeneity in responses across socio-economic groups, sometimes exceeding the aggregate estimates. As noted in Section 4, the shift-share IV design remains valid under such heterogeneity because it takes a convex average of different treatment effects. Hence, the shift-share IV design offers a robust way to measure the overall impact and incidence of wage subsidies, while micro regressions with appropriate controls reveal the underlying labor supply responses at the individual level.

[37]Cells with a below-median share of men do exhibit smaller elasticities for employment, hours, and labor earnings than their above-median counterparts, though the coefficients for total hours and labor earnings remain statistically significant. Sicsic (2022) similarly reports that labor earnings elasticities with respect to the net-of-average-tax rate in France are roughly twice as large for men (0.317) compared to women (0.156).

Figure 4: Micro responses to direct tax shocks, heterogeneity analysis



Notes: This table reports coefficients from IV regressions for the three-year change in the log of labor market outcomes for net-of-tax rates and net-of-participation-tax rates using the baseline specification. Labor market outcomes are defined by cells, each representing a combination of socio-economic group, local labor market, and period. Direct tax shocks are defined at the socio-economic group and period level. Each regression is weighted by the number of observations within each cell in the initial period. Local labor market outcomes include the hourly wage rate in panel (a), the employment rate in panel (b), the number of hours worked in panel (c), and total labor earnings in panel (d). Base-year controls include average hours worked and wage rates at the cell level in the initial year t. Standard errors are clustered at the socio-economic group-department level.

7 Conclusion

This paper provides novel causal estimates regarding the wage and employment effects of wage subsidies. It departs from the conventional assumption of the absence of equilibrium effects in the labor market by accounting for both labor demand and labor supply responses. Leveraging a unique combination of rich administrative data on individuals, a French reform in the wage subsidy schedule in 2015, and an innovative quasi-experimental research design, this paper quantifies wage and employment effects separately.

I find, at the local labor market level, that an increase in the generosity of wage subsidies increases the number of hours worked, albeit counterbalanced by a decline in the hourly wage rate, relative to the counterfactual situation of an absence of change in the wage subsidy schedule. Specifically, the labor market level elasticities for wages (respectively employment) are approximately zero for the net-of-tax rate, and close to -0.309 (respectively 0.270) with respect to the net-of-participation-tax rate. In summary, the wage and employment effects exhibit similar magnitudes but divergent signs, leading to labor earnings showing little responsiveness to wage subsidies. These responses suggest a pass-through of wage subsidies to wages equal to 31% on average, driven by labor supply responses at the extensive margin.

These results highlight the capacity of employers to capture a significant part of an increase in wage subsidies through reduced wage growth. Such findings have significant implications for the design of programs aimed at incentivizing individuals to increase their labor supply. There are hidden and incidental costs, as the target population may not fully benefit from these programs, particularly since they primarily target working-poor individuals and households. In this context, a negative income tax, as discussed by Rothstein (2010) can be more effective tool for redistributing resources to the lower parts of the income distribution. A binding minimum wage, set together with the wage subsidy, can also be an alternative redistribution mechanism (Vergara, 2023).

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Online Appendix - Not for Publication

A Tables

Table A.1: Distribution of the number of individuals across local labor markets

Mean	SD	p5	Median	p95	Min	Max
(a) Commuting zones						
602	967	82	302	1,772	30	12,134
(b) Departements						
1,902	1,383	380	1,600	4,550	182	8,479

Notes: This table summarizes the distribution of the number of individuals across local labor markets for base year t between 2011 and 2015, defined by commuting zones in panel (a) and départements in panel (b). All statistics are unweighted. The median number of observations per local labor market-year cell is 302 for commuting zones and 1,600 for départements.

Table A.2: Local labor markets summary statistics, commuting zone level

	Mean	SD	p5	Median	p95
(a) Three-year log-growth rates					
Labor earnings	0.071	0.022	0.033	0.072	0.102
Hours	-0.009	0.021	-0.044	-0.009	0.024
Wage rate	0.08	0.017	0.054	0.08	0.11
Employment rate	-0.003	0.019	-0.043	-0.001	0.026
(b) Start-of-period labor market characteristics					
Mean labor earnings (in euros)	17,168	597	16,126	17,203	18,215
Mean hours	1,376	105	1,178	1,399	1,526
Mean hours, cond. on working	1,587	44	1,517	1,587	1,655
Mean wage rate (in euros)	10.69	0.2	10.35	10.7	10.97
Mean employment rate	87%	5%	77%	88%	93%
Prop. working full-year	70%	6%	59%	70%	78%
Prop. working full-time	67%	6%	57%	68%	76%
Prop. close to the MW	9%	2%	6%	9%	13%
Prop. working in industry	11%	6%	4%	10%	21%
Prop. working in services	58%	8%	46%	58%	74%
(c) Start-of-period demographics					
Mean age	38	1	37	38	39
Prop. eligible to the wage subsidy	47%	6%	38%	46%	59%
Prop. in a couple	67%	6%	55%	67%	77%
Prop. with children	66%	5%	54%	66%	74%
(d) Sample size					
No. of LLM = 297; No. of periods = 5; No. of LLM-periods = 1,485.					

Notes: This table provides summary statistics for local labor markets defined as commuting zones. Panel (a) reports the three-year log-growth rates of labor market variables for the five time periods 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018; panel (b) shows characteristics of local labor markets for for base years between 2011 and 2015, and panel (c) includes demographic characteristics for base years between 2011 and 2015. Panel (d) presents sample size information. Close to the minimum wage is defined as having an hourly wage rate below the minimum wage plus €1. All statistics are weighted by each local labor market's share in the national population during the initial period. All monetary values are presented in real terms, with a base year of 2011.

Table A.3: Observed tax shocks and exposure measures summary statistics

	Mean	SD	p5	Median	p95	N
(a) Socio-economic groups: three-year tax shocks						
Net-of-participation-tax rates:						
$g_{n,t}^{1-ATR}$	-0.012	0.02	-0.044	-0.01	0.018	620
$g_{n,t}^{1-ATR}$ (resid. on period F.E)	0	0.017	-0.031	0.004	0.023	620
Net-of-tax rates:						
$g_{n,t}^{1-MTR}$	-0.027	0.042	-0.095	-0.031	0.045	620
$g_{n,t}^{1-MTR}$ (resid. on period F.E)	0	0.04	-0.061	-0.006	0.069	620
(b) Local labor markets: three-year exposure measures						
Net-of-participation-tax rates:						
$x_{l,t}^{1-ATR}$	-0.012	0.009	-0.022	-0.018	0.001	470
$x_{l,t}^{1-ATR}$ (resid. on period F.E)	0	0.002	-0.003	0	0.003	470
Net-of-tax rates:						
$x_{l,t}^{1-MTR}$	-0.027	0.013	-0.054	-0.023	-0.014	470
$x_{l,t}^{1-MTR}$ (resid. on period F.E)	0	0.003	-0.005	0	0.005	470
(c) Sample size						
Distribution of shares $s_{n,t}$:						
Effective sample size (1/HHI) = 243						
1/HHI across SE groups = 49						
Observation counts:						
No. of LLM = 94; No. of SE groups = 124; No. of periods = 5.						
Largest share = 0.86%						

Notes: This table summarizes the distribution of observed tax shocks and exposure measures over the the five time periods 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018. Panel (a) reports the distribution of shocks across socio-economic groups, panel (b) presents the distribution of exposure measures across local labor markets, and panel (c) provides the sample size. In both panels (a) and (b), statistics are reported separately for the net-of-participation-tax rates and the net-of-tax rates. Shocks and exposures are also residualized on period fixed effects. Shocks and exposures are calculated as three-year log differences, with base year t ranging from 2011 to 2015. Statistics in panel (a) are weighted by the shares $s_{n,t}$, and those in panel (b) are weighted by the shares $s_{l,t}$, representing each local labor market's share in the national population.

Table A.4: Distribution of the percentage of stayers across local labor markets and over time

Mean	SD	p5	Median	p95	N
		(a) Departements			
95%	3%	89%	96%	97%	470
		(b) Commuting zones			
94%	2%	90%	95%	97%	1,485

Notes: This table summarizes the distribution of the percentage of individuals who remained in the same local labor market between year t and $t + 3$, across local labor markets and periods for base years t between 2011 and 2015. In panel (a), local labor markets are defined as départements, and in panel (b), as commuting zones. All statistics are weighted by the share of each local labor market in the national observed population.

Table A.5: Shift-share IV estimates, commuting zone level

	Three-year log-growth rates		
	Hours	Wage rate	Labor earnings
	(1)	(2)	(3)
Equivalent shock-level exposure measures			
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	-0.080	0.038	-0.042
	(0.135)	(0.057)	(0.174)
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.300***	-0.252***	0.049
	(0.112)	(0.068)	(0.153)
Controls			
Socio-economic group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Local labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓
SSIV statistics			
No. of socio-economic groups-periods	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	78.6	78.6	78.6
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	284.3	284.3	284.3

Notes: This table reports coefficients from shift-share IV regressions for the three-year change in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. Local labor markets are defined as commuting zones. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (column (1)), the hourly wage rate (column (2)), and total labor earnings (column (3)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.6: Shift-share IV estimates, by period length

	Hours		Wage rate		Labor earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Equivalent shock-level exposure measures						
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	0.007	-0.125*	0.059	0.122	0.067	-0.003
	(0.100)	(0.072)	(0.086)	(0.075)	(0.160)	(0.102)
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.270***	0.333***	-0.309***	-0.304***	-0.038	0.029
	(0.093)	(0.038)	(0.067)	(0.058)	(0.142)	(0.059)
Controls						
Socio-economic group F.E	✓	✓	✓	✓	✓	✓
Period F.E	✓	✓	✓	✓	✓	✓
Local labor market F.E	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓
SSIV statistics						
No. of socio-economic groups-periods	620	620	620	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	57.9	48.8	57.9	48.8	57.9	48.8
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	237.8	196.6	237.8	196.6	237.8	196.6
Period length	3-year	2-year	3-year	2-year	3-year	2-year

Notes: This table reports coefficients from shift-share IV regressions for the three-year change (columns (1), (3) and (5)) and two-year change (columns (2), (4) and (6)) in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (columns (1) and (2)), the hourly wage rate (columns (3) and (4)), and total labor earnings (columns (5) and (6)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.7: Shift-share IV estimates, alternative specifications

	Three-year log-growth rates																	
	Hours						Wage rate						Labor earnings					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Equivalent shock-level exposure measures																		
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	0.020	0.007	0.013	0.025	0.088		0.048	0.059	0.044	0.064	-0.033		0.068	0.067	0.057	0.089	0.055	
	(0.106)	(0.100)	(0.108)	(0.104)	(0.069)		(0.087)	(0.086)	(0.093)	(0.087)	(0.130)		(0.156)	(0.160)	(0.169)	(0.164)	(0.139)	
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.214**	0.270***	0.247**	0.235**		0.272***	-0.299***	-0.309***	-0.294***	-0.294***		-0.294***	-0.085	-0.038	-0.046	-0.059		-0.022
	(0.094)	(0.093)	(0.098)	(0.096)		(0.082)	(0.072)	(0.067)	(0.074)	(0.070)		(0.060)	(0.144)	(0.142)	(0.152)	(0.146)		(0.125)
Controls																		
Children F.E			✓						✓						✓			
Couple F.E			✓						✓						✓			
Household income F.E			✓						✓						✓			
Socio-economic group F.E		✓		✓	✓	✓		✓		✓	✓	✓		✓		✓	✓	✓
Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local labor market F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Additional base-year controls				✓						✓						✓		
SSIV statistics																		
No. of socio-economic groups-periods	620	620	620	620	620	620	620	620	620	620	620	620	620	620	620	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	35.7	57.9	41.7	55.5	112.6		35.7	57.9	41.7	55.5	112.6		35.7	57.9	41.7	55.5	112.6	
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	128.2	237.8	166.3	233.1		468.5	128.2	237.8	166.3	233.1		468.5	128.2	237.8	166.3	233.1		468.5

Notes: This table reports coefficients from alternative shift-share IV regressions for the three-year change in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (columns (1)-(6)), the hourly wage rate (columns (7)-(12)), and total labor earnings (columns (9)-(16)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Additional base-year controls include the proportion of individuals close to the minimum wage, those working full-year, and those working full-time. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.8: Shift-share IV estimates, alternative samples

	Three-year log-growth rates								
	Hours			Wage rate			Labor earnings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equivalent shock-level exposure measures									
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	0.007	-0.040	-0.064	0.059	-0.020	-0.038	0.067	-0.060	-0.101
	(0.100)	(0.091)	(0.090)	(0.086)	(0.090)	(0.085)	(0.160)	(0.153)	(0.146)
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.270***	0.234***	0.232***	-0.309***	-0.222***	-0.210***	-0.038	0.012	0.023
	(0.093)	(0.087)	(0.083)	(0.067)	(0.058)	(0.057)	(0.142)	(0.124)	(0.119)
Controls									
Socio-economic group F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local labor market F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
SSIV statistics									
No. of socio-economic groups-periods	620	620	620	620	620	620	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	57.9	59.9	64.0	57.9	59.9	64.0	57.9	59.9	64.0
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	237.8	231.5	227.6	237.8	231.5	227.6	237.8	231.5	227.6
Wage rate threshold in t (in euros)	14	14.5	15	14	14.5	15	14	14.5	15

Notes: This table reports coefficients from shift-share IV regressions using alternative samples for the three-year change in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. Columns (1), (4) and (7) reports coefficient with the sample restriction that pre-tax hourly wages are below €14 per hour in the initial year t, columns (2), (5) and (8) report coefficients with the sample restriction that pre-tax hourly wages are below €14.50 per hour, and columns (3), (6) and (9) report coefficients with the sample restriction that pre-tax hourly wages are below €15 per hour. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (column (1)), the hourly wage rate (column (2)), and total labor earnings (column (3)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.9: Correlation between exposure measures and simulated shocks with payroll taxes and baseline exposure measures and shocks

	Exposure measure with payroll taxes				*Simulated shock with payroll taxes*			
	NTR		NPTR		NTR		NPTR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baseline exposure measure	0.789***	0.790***	1.00***	1.00***				
	(0.011)	(0.011)	(0.0007)	(0.0007)				
Baseline simulated shock					1.05***	0.994***	1.15***	1.00***
					(0.008)	(0.002)	(0.021)	(0.0002)
Controls								
Socio-economic group F.E		✓		✓		✓		✓
Period F.E		✓		✓		✓		✓
Local labor market F.E	✓	✓	✓	✓				
Base-year controls	✓	✓	✓	✓				
Shift-share statistics								
No. of socio-economic groups-periods	620	620	620	620	620	620	620	620
Adjusted R^2	0.920	0.903	1.00	1.00	0.968	1.00	0.776	1.00

Notes: This table reports coefficients from OLS regressions of the three-year change exposure measures/simulated tax shocks with payroll taxes on their corresponding baseline versions. All regressions are weighted by each labor market's share in the national population in the initial period. NTR and NPTR denotes the net-of-tax rate and net-of-participation-tax rate, respectively. Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level regressions to obtain exposure-robust standard errors and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.10: Shift-share IV estimates, gross labor earnings and wages

	Three-year log-growth rates		
	Hours (1)	Wage rate (2)	Labor earnings (3)
Equivalent shock-level exposure measures			
Net-of-tax rates, $\bar{x}_{nt}^{1-MTR}$	0.009	0.062	0.072
	(0.121)	(0.097)	(0.185)
Net-of-participation-tax rates, $\bar{x}_{nt}^{1-ATR}$	0.270***	-0.287***	-0.017
	(0.089)	(0.055)	(0.124)
Controls			
Socio-economic group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Local labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓
SSIV statistics			
No. of socio-economic groups-periods	620	620	620
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	53.6	53.6	53.6
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	236.0	236.0	236.0

Notes: This table reports coefficients from shift-share IV regressions for the three-year change in the log of local labor market outcomes on the exposure measures, weighted by each labor market's share in the national population in the initial period. The exposure measures for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the number of hours worked (column (1)), the gross hourly wage rate (column (2)), and total gross labor earnings (column (3)). Base-year controls include average hours worked and wage rates at the local labor market level in the initial year t. Results are derived from equivalent shock-level IV regressions to obtain exposure-robust standard errors, F-statistics, and to incorporate socio-economic group fixed effects. Standard errors are clustered at the socio-economic group level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

Table A.11: Labor markets summary statistics, local labor market–socio-economic group–period level

	Mean	SD	p5	Median	p95
(a) Three-year log-growth rates					
Labor earnings	0.087	0.175	-0.046	0.058	0.266
Hours	0.003	0.169	-0.137	-0.021	0.172
Wage rate	0.084	0.042	0.027	0.08	0.158
Employment rate	0.008	0.084	-0.1	0	0.125
(b) Start-of-period labor market characteristics					
Mean labor earnings (in euros)	17,505	3,804	10,237	18,104	22,385
Mean hours	1,417	356	679	1,504	1,865
Mean hours, cond. on working	1,627	278	1,100	1,705	1,875
Mean wage rate (in euros)	10.68	0.97	9.04	10.66	12.14
Mean employment rate	87%	14%	58%	91%	100%
Prop. working full-year	72%	20%	29%	78%	96%
Prop. working full-time	69%	18%	35%	71%	98%
Prop. close to the MW	8%	9%	0%	6%	27%
(c) Sample size					
No. of LLM-SE groups-periods = 21,122.					

Notes: This table provides summary statistics at the local labor market–socio-economic group–period level. Panel (a) reports the three-year log-growth rates of labor market variables for the five time periods 2011–2014, 2012–2015, 2013-2016, 2014-2017, 2015–2018; panel (b) shows characteristics of local labor markets for for base years between 2011 and 2015, Panel (c) presents sample size information. Close to the minimum wage is defined as having an hourly wage rate below the minimum wage plus €1. All statistics are weighted by the number of observations in each cell. All monetary values are presented in real terms, with a base year of 2011.

Table A.12: Micro responses to direct tax shocks, alternative specifications

	Three-year log-growth rates																			
	Wage rate					Employment					Hours					Labor earnings				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Tax shocks																				
Net-of-tax rates, g_{nt}^{1-MTR}	-0.011	-0.016*	-0.013	-0.011		-0.007	-0.047***	-0.028*	-0.002		0.045*	-0.048***	0.009	0.055**		0.035	-0.064***	-0.004	0.045*	
	(0.011)	(0.009)	(0.010)	(0.011)		(0.017)	(0.013)	(0.015)	(0.017)		(0.024)	(0.018)	(0.021)	(0.024)		(0.024)	(0.018)	(0.021)	(0.024)	
Net-of-participation-tax rates, g_{nt}^{1-ATR}	-0.021	-0.004	0.001		-0.015	0.159***	0.090***	0.126***		0.163***	0.314***	0.045	0.145***		0.288***	0.298***	0.042	0.146***		0.278***
	(0.031)	(0.021)	(0.023)		(0.031)	(0.051)	(0.030)	(0.035)		(0.049)	(0.071)	(0.040)	(0.047)		(0.069)	(0.069)	(0.039)	(0.046)		(0.067)
Controls																				
HH income group-Couple-Period F.E	✓			✓	✓	✓			✓	✓	✓			✓	✓	✓			✓	✓
Spline MW-Period F.E			✓					✓					✓					✓		
LLM-SE group F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LLM-Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
IV statistics																				
No. of observations	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423	20,423
F-test (1st stage), $\tilde{g}_{nt}^{1-MTR}$	20,439.0	24,658.9	21,096.5	35,302.7		20,439.0	24,658.9	21,096.5	35,302.7		20,439.0	24,658.9	21,096.5	35,302.7		20,439.0	24,658.9	21,096.5	35,302.7	
F-test (1st stage), $\tilde{g}_{nt}^{1-ATR}$	68,297.3	95,039.1	95,219.6		131,278.6	68,297.3	95,039.1	95,219.6		131,278.6	68,297.3	95,039.1	95,219.6		131,278.6	68,297.3	95,039.1	95,219.6		131,278.6

Notes: This table reports coefficients from alternative IV regressions for the three-year change in the log of labor market outcomes on direct tax shocks. Labor market outcomes are defined by cells, each representing a combination of socio-economic group, local labor market, and period. Direct tax shocks are defined at the socio-economic group and period level. Each regression is weighted by the number of observations within each cell in the initial period. The direct tax shocks for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the hourly wage rate (columns (1)-(5)), the employment rate (columns (6)-(10)), the number of hours worked (columns (11)-(15)), and total labor earnings (columns (16)-(20)). Base-year controls include average hours worked and wage rates at the cell level in the initial year t. Standard errors are clustered at the socio-economic group-department level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

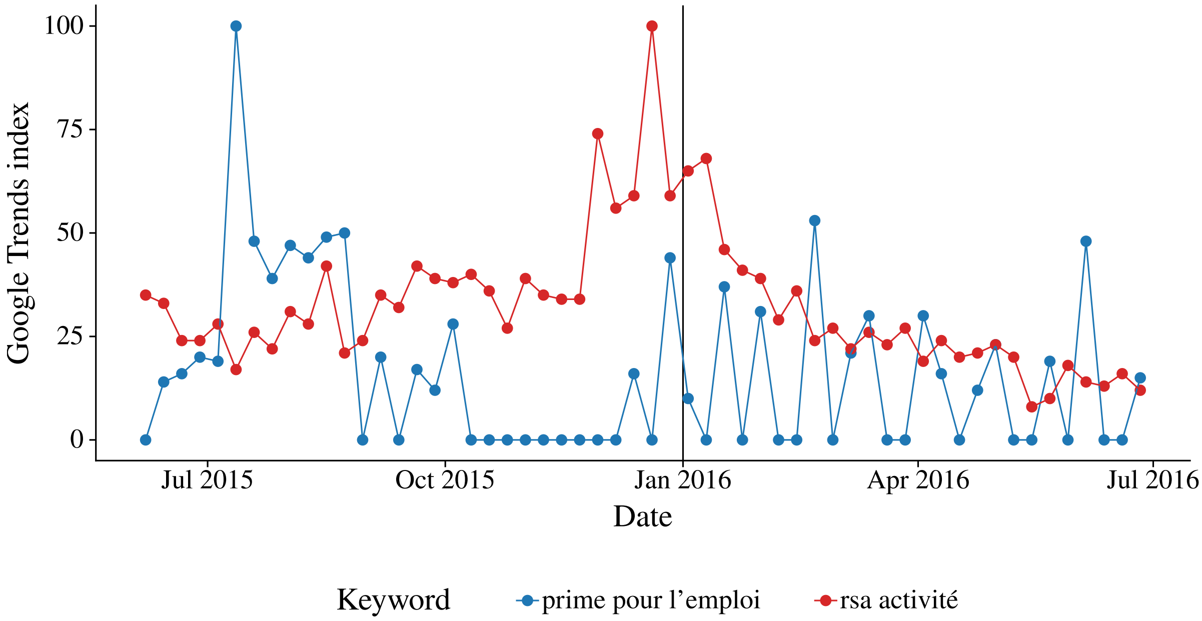
Table A.13: Micro responses to direct tax shocks, alternative shocks

	Three-year log-growth rates			
	Wage rate (1)	Employment (2)	Hours (3)	Labor earnings (4)
Tax shocks				
Net-of-tax rates, g_{lnt}^{1-MTR}	-0.004	-0.002	0.042*	0.040*
	(0.010)	(0.017)	(0.023)	(0.023)
Net-of-participation-tax rates, g_{lnt}^{1-ATR}	-0.025	0.132***	0.221***	0.203***
	(0.030)	(0.049)	(0.067)	(0.066)
Controls				
HH income group-Couple-Period F.E	✓	✓	✓	✓
LLM-SE group F.E	✓	✓	✓	✓
LLM-Period F.E	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓
IV statistics				
No. of observations	20,423	20,423	20,423	20,423
F-test (1st stage), $\tilde{g}_{lnt}^{1-MTR}$	7,100.3	7,100.3	7,100.3	7,100.3
F-test (1st stage), $\tilde{g}_{lnt}^{1-ATR}$	4,999.2	4,999.2	4,999.2	4,999.2

Notes: This table reports coefficients from IV regressions for the three-year change in the log of labor market outcomes on direct tax shocks. Labor market outcomes are defined by cells, each representing a combination of socio-economic group, local labor market, and period. Direct tax shocks are defined at the local level market, socio-economic group and period level. Each regression is weighted by the number of observations within each cell in the initial period. The direct tax shocks for net-of-tax rates and net-of-participation-tax rates are instrumented with their corresponding instruments. Local labor market outcomes include the hourly wage rate in column (1), the employment rate in column (2), the number of hours worked in column (3), and total labor earnings in column (4). Base-year controls include average hours worked and wage rates at the cell level in the initial year t. Standard errors are clustered at the socio-economic group-department level. Significance levels are indicated as follows: ***0.01, **0.05, *0.1.

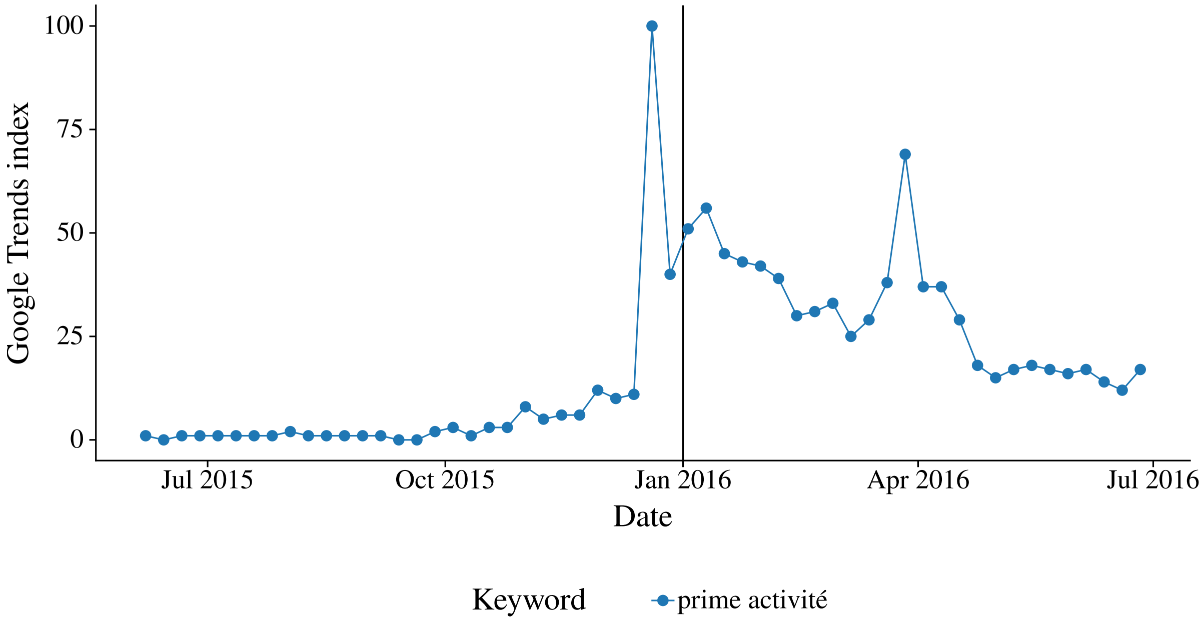
B Figures

Figure B.1: Evolution of the Google Trends index for the two before-reform wage subsidy programs over time



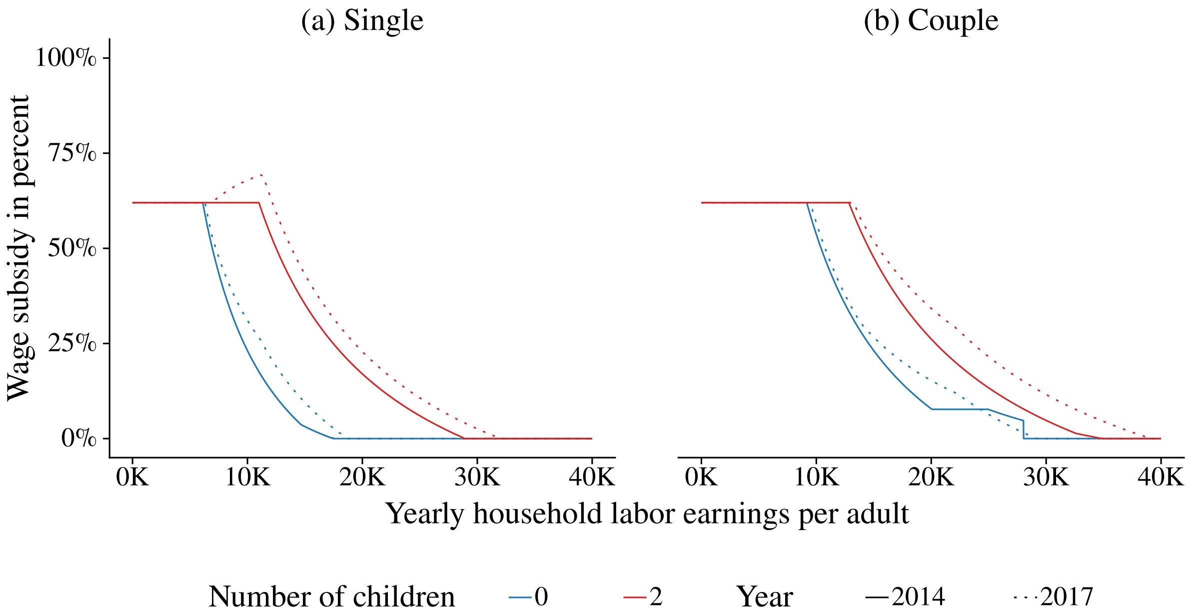
Notes: The figure plots times series for the Google Trends index for the two before-reform wage subsidy programs. More precisely, the two keywords are "prime pour l'emploi" and "rsa activité". Each index is the result of a normalization between 0 and 100 of the number of search for these terms. 100 indicates the day where the number of search are the highest. The vertical black line is the date of implementation of the reform. Data and methodology are available on Google Trends.

Figure B.2: Evolution of the Google Trends index for the after-reform wage subsidy program over time



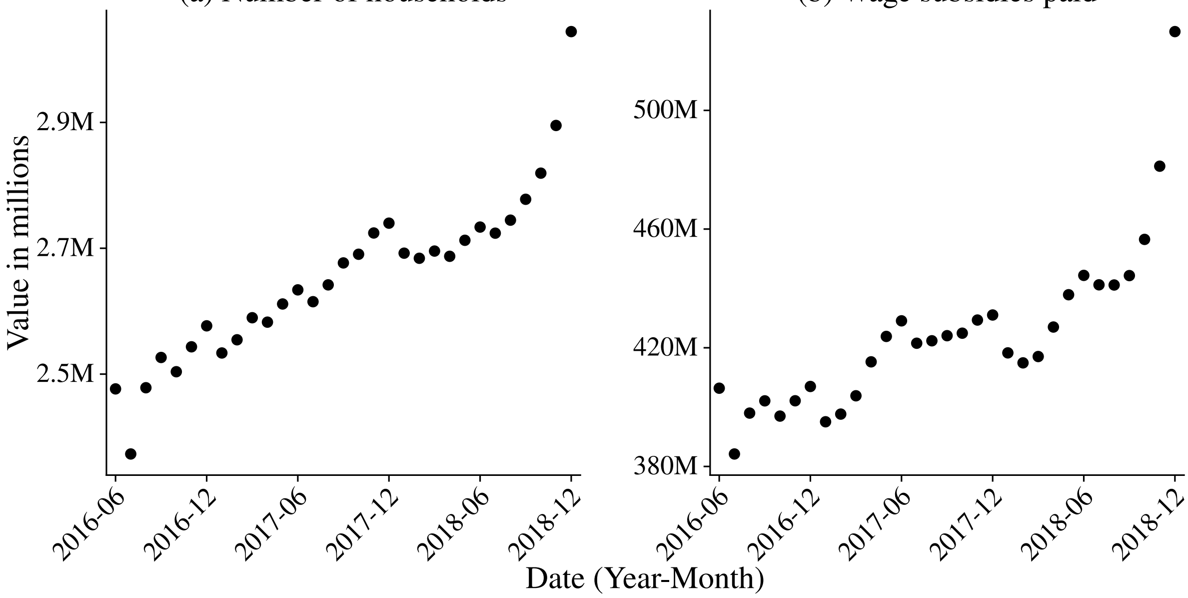
Notes: The figure plots times series for the Google Trends index for the two before-reform wage subsidy programs. More precisely, the keyword is "prime activité". Each index is the result of a normalization between 0 and 100 of the number of search for these terms. 100 indicates the day where the number of search are the highest. The vertical black line is the date of implementation of the reform. Data and methodology are available on Google Trends.

Figure B.3: Wage subsidy schedule, in percent of labor earnings



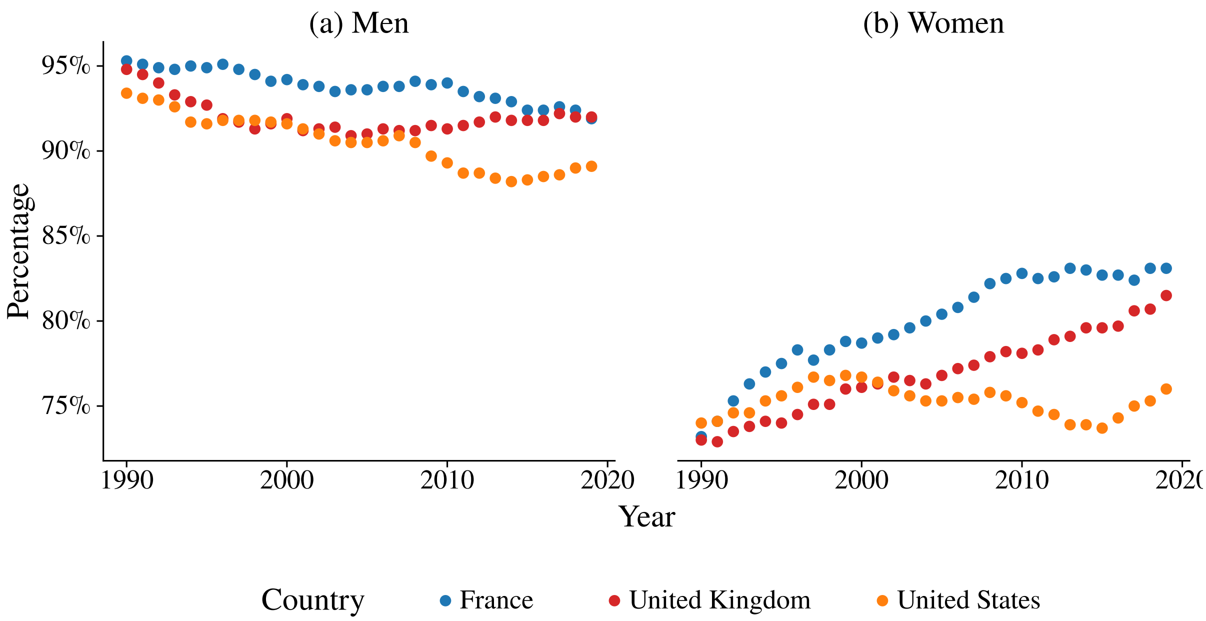
Notes: The figure plots the wage subsidy amount that a household is eligible for, expressed in percent of labor earnings, based on its yearly household labor earnings per adult, expressed in thousands of euros. Panel (a) focuses on single individuals, while panel (b) focuses on couples. Within each panel, the wage subsidy schedule is presented separately for households with varying numbers of children (no children in blue and two children in red) and for two different years (2014 represented by solid lines and 2017 by dotted lines). The wage subsidy reform was implemented for incomes starting in 2016. The simulation uses Openfisca, an open-source taxes and benefits simulator. The simulation assumes that labor earnings are the sole source of income and that labor earnings are evenly distributed among partners in a couple, and full take-up of wage subsidy programs.

Figure B.4: Monthly number of households and total spending for the *Prime d'Activité*



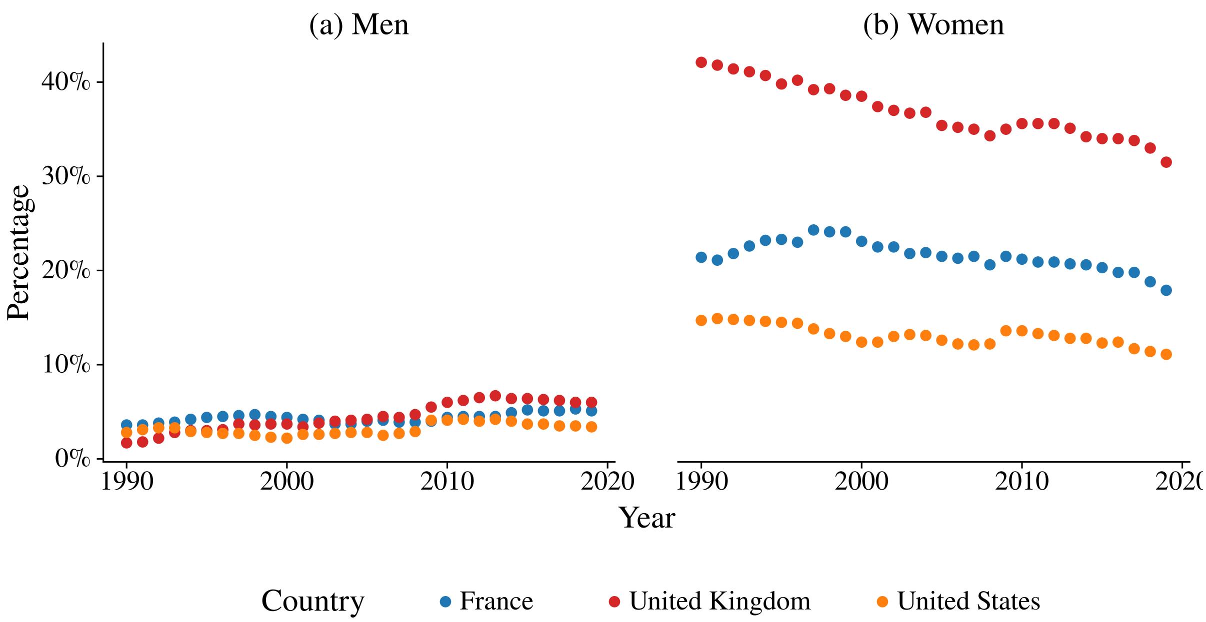
Notes: The figure displays the number of households receiving the *Prime d'Activité* in panel (a) and the total wage subsidies paid in panel (b) for each month between June 2016 and December 2018. Both are expressed in millions.

Figure B.5: Labor force participation, by sex



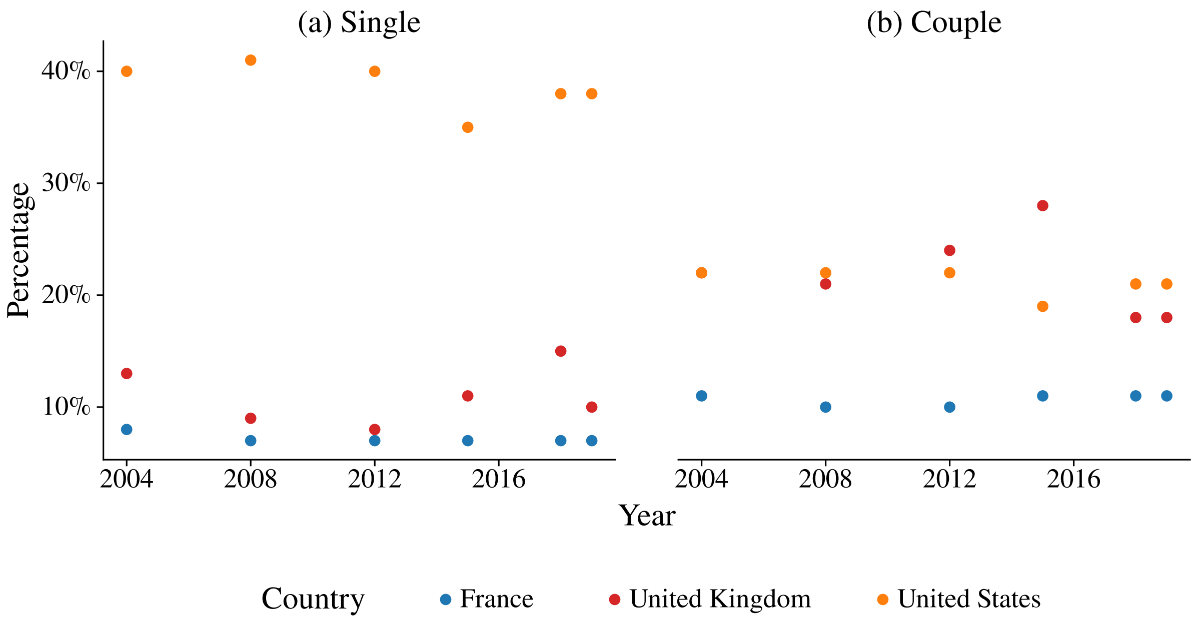
Notes: The figure plots times series of labor force participation rates for France, the United Kingdom and the United States at the yearly level. The labour force participation rates is calculated as the labour force divided by the total working-age population, separately for the men (panel (a)) and for women (panel (b)). The reference population is people aged 25 to 54. Data and methodology are available on OECD.Stat.

Figure B.6: Share of employed in part-time employment, by sex



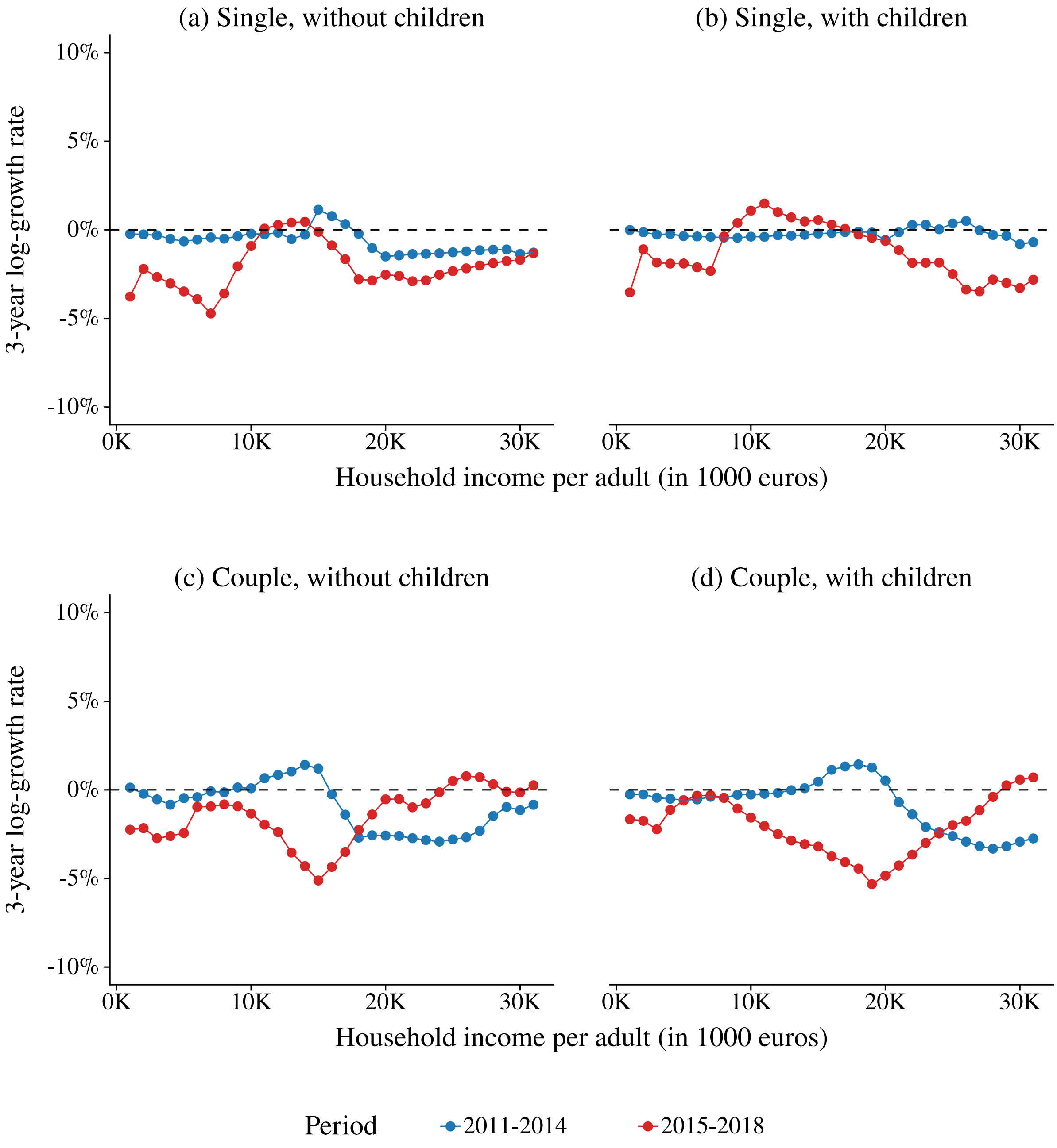
Notes: The figure plots times series of labor force participation rates for France, the United Kingdom and the United States at the yearly level. Part-time employment is defined as people in employment (whether employees or self-employed) who usually work less than 30 hours per week in their main job. Employed people are those who report that they have worked in gainful employment for at least one hour in the previous week or who had a job but were absent from work during the reference week while having a formal job attachment. The shares are calculated as the labour force divided by the total working-age population, separately for the men (panel (a)) and for women (panel (b)). The reference population is people aged 25 to 54. Data and methodology are available on OECD.Stat.

Figure B.7: Childcare costs in net household income for parents with two children



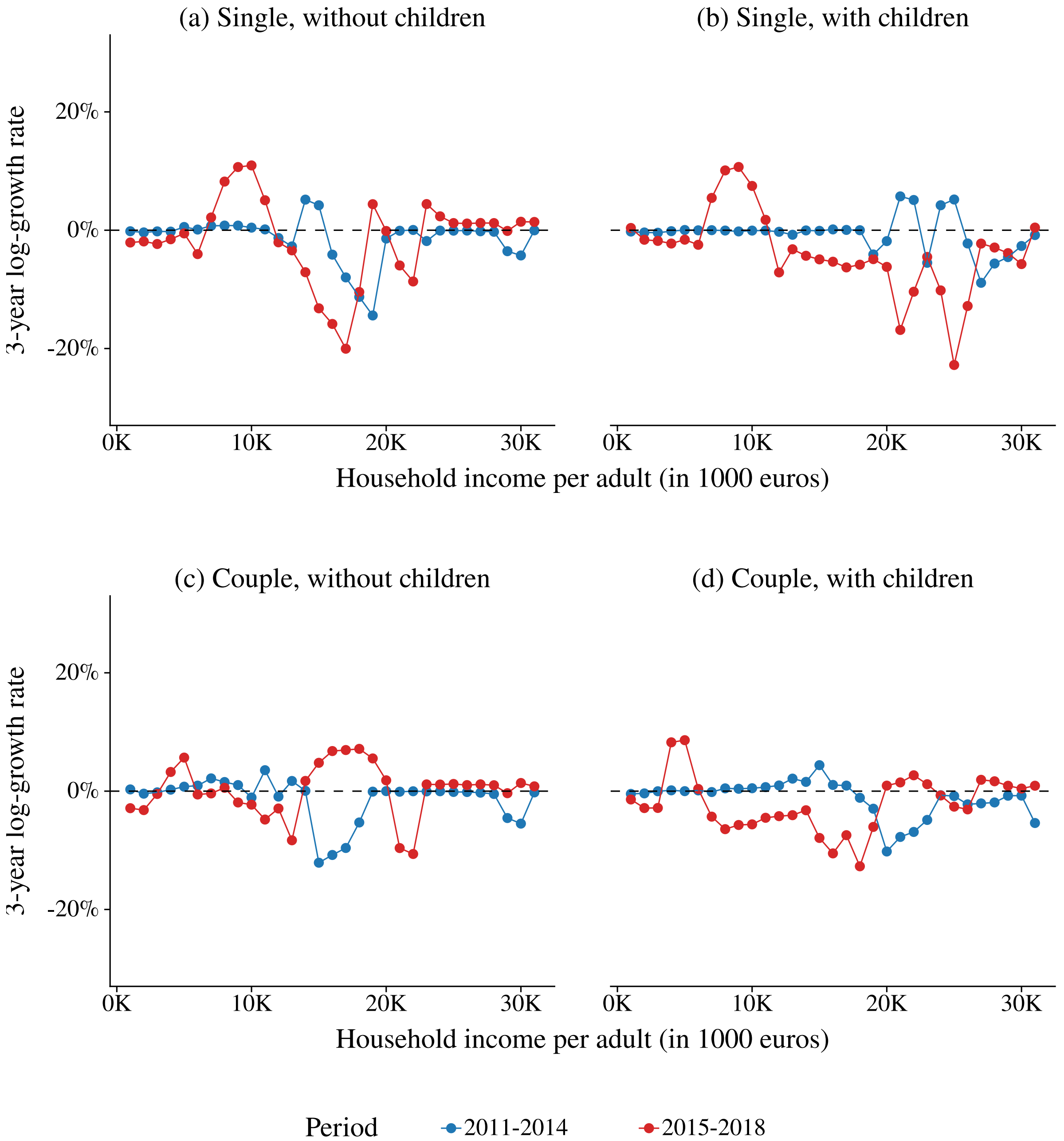
Notes: The figure plots times series of net childcare costs in percentage of net household income for France, the United Kingdom and the United States at the yearly level. Parents earn the average wage at full-time work. The net childcare cost is the difference between the gross childcare fee and childcare benefits (any types). Panel (a) plots the percentage for single parents and panel (b) for couples. Data and methodology are available on OECD.Stat.

Figure B.8: Distribution of shocks $\tilde{g}_{n,t}^{1-ATR}$ across socio-economic groups and periods



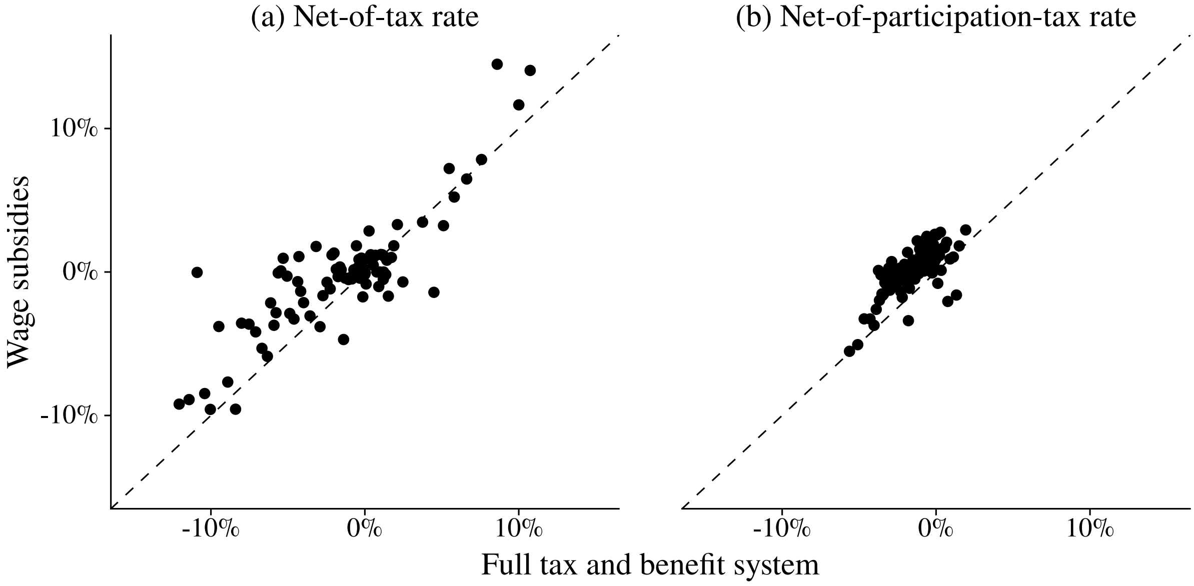
Notes: The figure plots the three-year change in the log of the net-of-participation-tax rate at the socio-economic group level, for the 2011-1014 and 2015-2018 periods. The simulated tax rates take into account the full tax and redistribution system. The socio-economic groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis).

Figure B.9: Distribution of shocks $\tilde{g}_{n,t}^{1-MTR}$ across socio-economic groups and periods



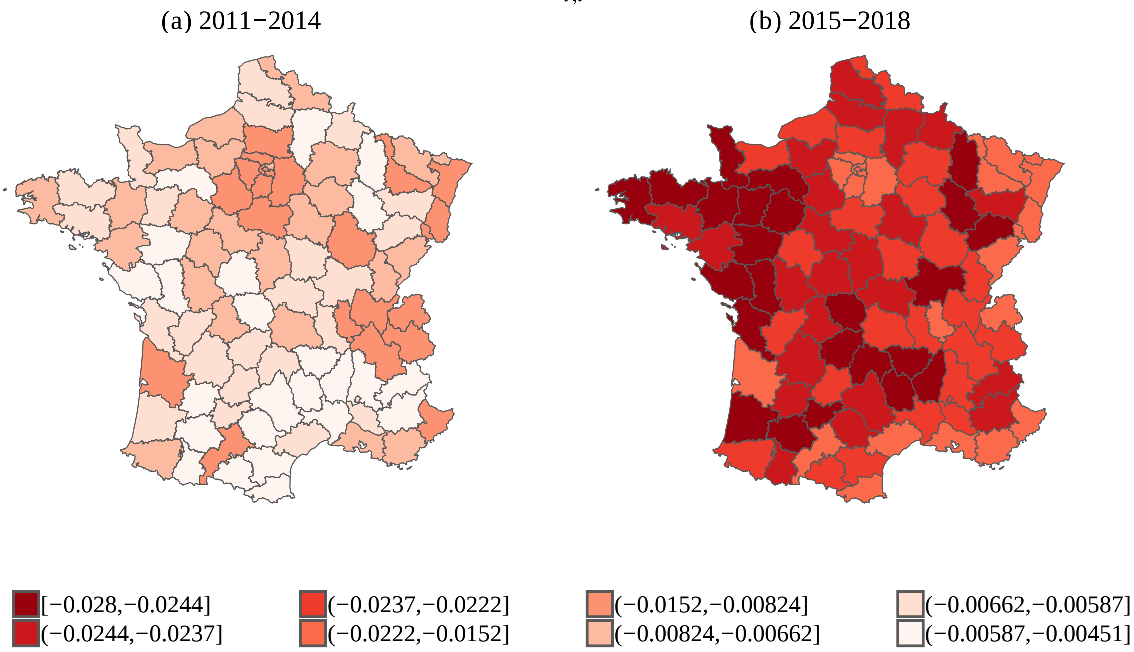
Notes: The figure plots the three-year change in the log of the net-of-tax rate at the socio-economic group level, for the 2011-1014 and 2015-2018 periods. The simulated tax rates take into account the full tax and redistribution system. The socio-economic groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis).

Figure B.10: Correlation between simulated tax shocks at the socio-economic group level



Notes: The figure displays the correlation between the three-year changes in tax shocks at the socio-economic group level, pooling base years t from 2011 to 2015. The y-axis represents changes considering only wage subsidies, while the x-axis represents changes considering the full tax and benefit system. Results are reported separately for the net-of-tax rate (panel (a)) and the net-of-participation-tax rate (panel (b)). Each dot represents 1% of the data. Results from an OLS regression (with intercept) reports a correlation coefficient of 0.86 for the net-of-tax rate and of 0.76 for the net-of-participation-tax rate. The 45-degree line is dashed.

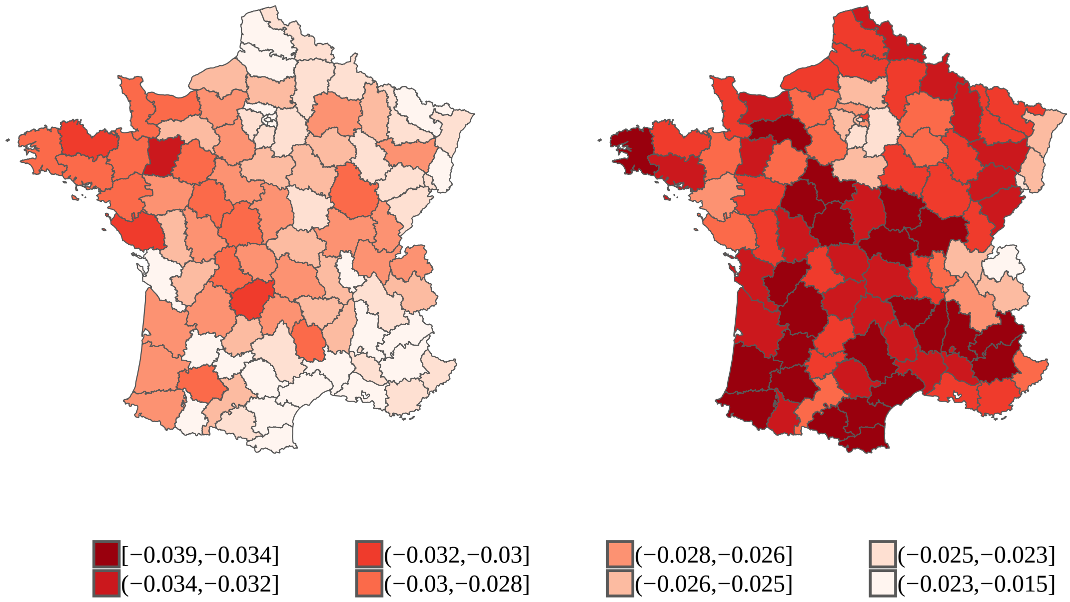
Figure B.11: Distribution of exposure measures $z_{l,t}^{1-ATR}$ across local labor markets and periods



Notes: The figure plots the three-year change in the log of the net-of-participation-tax rate across local labor markets (départements), for the 2011-1014 (panel (a)) and 2015-2018 (panel (b)) periods.

Figure B.12: Distribution of exposure measures $z_{l,t}^{1-MTR}$ across local labor markets and periods

(a) 2011−2014 (b) 2015−2018



Notes: The figure plots the three-year change in the log of the net-of-tax rate across local labor markets (départements), for the 2011-1014 (panel (a)) and 2015-2018 (panel (b)) periods.

C Models of Wage Subsidies with Equilibrium Effects

C.1 Baseline Model

Agents. Individuals differ along two key dimensions: the local labor market to which they belong, indexed by $l = 1, \ldots, L$, and their socio-economic group, indexed by n. Socio-economic groups are independent of local labor market conditions and are functions of individual labor earnings, total household income, marital status and number of children. They collectively determine the level of taxes and benefits each group face, making these socio-economic groups proxies for the intensity of treatment from subsidy reforms.

Labor demand. Labor is the only input factor used to produce, and both the output and labor markets operate under perfect competition. A representative firm produces F with constant elasticity of substitution between the different labor markets. The firm's optimal labor choices solve the following profit maximization problem:

$$\max_{\{H_k\}_k} \pi = \left(\sum_{k=1}^{L} \beta_k H_k^{\frac{1+\eta}{\eta}} \right)^{\frac{\eta}{1+\eta}} - \sum_{k=1}^{L} w_k H_k.$$

The first component represents production F, and the second component represents the cost associated with it. w_k and H_k are the wage rate and labor demand in labor market k, and η is the elasticity of substitution between different local labor markets. The labor demand for local labor market l is $H_l = \varphi(\boldsymbol{w})^{-1} \beta_l^{-\eta} w_l^{\eta}$, where $\varphi(\boldsymbol{w})$ is an aggregate demand component common to all labor markets. The growth rate of the wage rate w_l is given by:

$$\frac{\mathrm{d}w_l}{w_l} = \frac{1}{\eta} \cdot \frac{\mathrm{d}\varphi(\boldsymbol{w})}{\varphi(\boldsymbol{w})} + \frac{1}{\eta} \cdot \frac{\mathrm{d}H_l}{H_l}. \tag{11}$$

Labor supply. Individuals who want to participate in the labor market incur an entry cost $q_{l,n}$. Once they decide to participate, they then choose the number of hours worked $h_{l,n}$. Individuals maximize their utility, denoted as $U(c_{l,n}, h_{l,n}) = v(c_{l,n}, h_{l,n}) - q_{l,n} 1 \left[h_{l,n} > 0 \right]$, subject to the budget constraint $c_{l,n} = w_l h_{l,n} - T_n(w_l h_{l,n})$. Here, $c_{l,n}$ represents disposable income and $T_n(w_l h_{l,n})$ represents taxes and benefits. Note that the tax function is indexed only by socio-economic group n because the tax schedule is defined at the national level. Intuitively, two individuals with similar characteristics (same individual labor earnings, total household income, marital status, and number of children) will have similar taxes and benefits regardless of their location.

The optimal number of hours worked and participation rate are respectively equal to $h_{l,n} = h(w_l(1 - \mathrm{MTR}_n))$ and $P_{l,n} = P(w_l h_{l,n}(1 - \mathrm{ATR}_n))$. For simplicity, I make the assumption of homogeneity in compensated elasticity of labor supply, denoted as ε^C, and participation elasticity, denoted as ε^P, across all groups.

Labor supply at the labor market level. In a given labor market, a socio-economic group has $M_{l,n}$ potential workers, such that the labor supply for the group (l,n) is $H_{l,n} = M_{l,n}P_{l,n}h_{l,n}$, while the overall labor supply in labor market l is given by $H_l = \sum_n H_{l,n}$. The growth rate in labor supply at the market level is given by:

$$\frac{\mathrm{d}H_l}{H_l} = \sum_n \frac{H_{l,n}}{H_l}\frac{\mathrm{d}P_{l,n}}{P_{l.n}} + \sum_n \frac{H_{l,n}}{H_l}\frac{\mathrm{d}h_{l,n}}{h_{l,n}} \tag{12}$$

$$\frac{\mathrm{d}h_{l,n}}{h_{l,n}} = \varepsilon^c\left[\frac{\mathrm{d}w_l}{w_l} + \frac{\mathrm{d}(1-\mathrm{MTR}_n)}{1-\mathrm{MTR}_n}\right] \tag{13}$$

$$\frac{\mathrm{d}P_{l,n}}{P_{l,n}} = \varepsilon^p\left[\frac{\mathrm{d}w_l}{w_l} + \frac{\mathrm{d}h_{l,n}}{h_{l,n}} + \frac{\mathrm{d}(1-\mathrm{ATR}_n)}{1-\mathrm{ATR}_n}\right]. \tag{14}$$

Wage and employment effects of wage subsidies. Using equations (11)-(14) and approximating and defining the growth rate of a variable v by $g^v = \Delta\ln(v)$, the wage and employment effects of wage subsidies are given by:

$$g_l^w = \alpha^w + \beta^w x_l^{1-MTR} + \gamma^w x_l^{1-ATR} \quad \text{and} \quad g_l^H = \alpha^H + \beta^H x_l^{1-MTR} + \gamma^H x_l^{1-ATR}.$$

They both depends on the market exposure to changes in the marginal tax rates and average tax rates defined by the following weighted averages:

$$x_l^{1-MTR} = \sum_g s_{l,n} g_n^{1-MTR} \quad \text{and} \quad x_l^{1-ATR} = \sum_g s_{l,n} g_n^{1-ATR},$$

where $s_{l,n} = H_{l,n}/H_l$ is the share of socio-economic group n in total labor supply of labor market l. α^w and α^L are common shocks to all local labor markets. The parameters of interest are the labor market level elasticities β^w, β^H, γ^w, and γ^H, which themselves depend on a set of structural parameters:

$$\beta^w = \frac{\varepsilon^c(1+\varepsilon^p)}{\chi}, \quad \gamma^w = \frac{\varepsilon^p}{\chi}, \quad \beta^H = \eta\beta^w, \quad \gamma^H = \eta\gamma^w.$$

with $\chi = \eta - \varepsilon^c - \varepsilon^p - \varepsilon^c\varepsilon^p$, $\alpha^w = (1/\chi)\cdot \mathrm{d}\varphi(\boldsymbol{w})/\varphi(\boldsymbol{w})$ and $\alpha^H = [(\eta-\chi)/\chi]\cdot \mathrm{d}\varphi(\boldsymbol{w})/\varphi(\boldsymbol{w})$.

C.2 Model with Heterogeneous Labor Demand

I extend the baseline model to a framework in which the firm has heterogeneous labor demand across local labor markets, while keeping the labor supply side the same.

Labor demand. A representative firm produces F with a nested CES production function. There is a constant elasticity of substitution between labor markets, η, and a constant elasticity of substitution between workers within each labor markets, η_l. The firm's optimal labor choices solve the cost minimization problem:

$$\max_{\{H_{k,n}\}_{(k,n)}} \quad \pi = F - C$$

$$F = \left(\sum_{k=1}^{L} \beta_k F_k^{\frac{1+\eta}{\eta}}\right)^{\frac{\eta}{1+\eta}}, \quad F_k = \left(\sum_n \beta_{k,n} H_{k,n}^{\frac{1+\eta_k}{\eta_k}}\right)^{\frac{\eta_k}{1+\eta_k}}, \quad C = \sum_{k=1}^{L} \sum_n w_{k,n} H_{k,n}$$

with $w_{l,n}$ and $H_{l,n}$ the wage rate and labor demand for socio-economic group n in labor market l. The first-order condition to this maximization problem is:

$$\frac{\partial \pi}{\partial F_l} \frac{\partial F_l}{\partial H_{l,n}} = \frac{\partial C}{\partial H_{l,n}}$$

$$\frac{\partial \pi}{\partial F_l} = \beta_l F_l^{\frac{1}{\eta}} \varphi(\boldsymbol{w})^{-1}, \quad \frac{\partial F_l}{\partial H_{l,n}} = \beta_{l,n} H_{l,n}^{\frac{1}{\eta_l}} \varphi_l(\boldsymbol{w}_l)^{-1}, \quad \frac{\partial C}{\partial H_{l,n}} = w_{l,n}$$

with $\varphi(\boldsymbol{w})$ an aggregate demand component common to all local labor markets and $\varphi_l(\boldsymbol{w}_l)$ an aggregate demand component common to all groups within a local labor market. The inverse demand function for group n in labor market l is defined as follows:

$$w_{l,n} = \varphi(\boldsymbol{w}) \cdot \varphi_l(\boldsymbol{w}_l) \cdot \beta_l \cdot \beta_{l,n} \cdot F_l^{\frac{1}{\eta}} \cdot H_{l,n}^{\frac{1}{\eta_l}}.$$

The growth in wage rate for socio-economic group n in labor market l is then defined by:

$$\frac{\mathrm{d}w_{l,n}}{w_{l,n}} = \frac{\mathrm{d}\varphi(\boldsymbol{w})}{\varphi(\boldsymbol{w})} + \frac{\mathrm{d}\varphi_l(\boldsymbol{w}_l)}{\varphi_l(\boldsymbol{w}_l)} + \frac{1}{\eta} \cdot \frac{\mathrm{d}F_l}{F_l} + \frac{1}{\eta_l} \cdot \frac{\mathrm{d}H_{l,n}}{H_{l,n}} \tag{15}$$

$$\frac{\mathrm{d}F_l}{F_l} = \sum_n \frac{\beta_{l,n} H_{l,n}^{\frac{1+\eta_l}{\eta_l}} \varphi_l(\boldsymbol{w}_l)}{F_l} \frac{\mathrm{d}H_{l,n}}{H_{l,n}}. \tag{16}$$

Labor supply. Labor supply is defined similarly to the case with homogeneous labor demand. The growth rate of the labor supply function for group (l, n) is given by:

$$\frac{\mathrm{d}H_{l,n}}{H_{l,n}} = \xi \frac{\mathrm{d}w_{l,n}}{w_{l,n}} + \varepsilon^c (1 + \varepsilon^p) \frac{\mathrm{d}(1 - \mathrm{MTR}_n)}{1 - \mathrm{MTR}_n} + \varepsilon^p \frac{\mathrm{d}(1 - \mathrm{ATR}_n)}{1 - \mathrm{ATR}_n}, \tag{17}$$

where $\xi = \varepsilon^c + \varepsilon^p + \varepsilon^c \varepsilon^p$.

Aggregation at the local labor market level. I define the average wage rate at the local labor market level as follows:

$$w_l = \frac{\sum_n w_{l,n} H_{l,n}}{H_l},$$

such that the growth rate of the average wage rate is given by:

$$\begin{aligned}\frac{\mathrm{d}w_l}{w_l} &= \sum_n \frac{w_{l,n}}{w_l}\frac{H_{l,n}}{H_l}\frac{\mathrm{d}w_{l,n}}{w_{l,n}} + \sum_n \frac{w_{l,n}}{w_l}\frac{H_{l,n}}{H_l}\frac{\mathrm{d}H_{l,n}}{H_{l,n}} - \frac{\mathrm{d}H_l}{H_l}\\ &= \sum_n \frac{w_{l,n}}{w_l}\frac{H_{l,n}}{H_l}\frac{\mathrm{d}w_{l,n}}{w_{l,n}} + \sum_n \left(\frac{w_{l,n}}{w_l} - 1\right)\frac{H_{l,n}}{H_l}\frac{\mathrm{d}H_{l,n}}{H_{l,n}}\end{aligned}$$

Using equations (15)-(17) together with the previous condition, the growth in the average hourly wage rate is equal to:

$$\frac{\mathrm{d}w_l}{w_l} = \alpha_l^w + \sum_n \beta_{l,n}^w s_{l,n}\frac{\mathrm{d}(1-\mathrm{MTR}_n)}{1-\mathrm{MTR}_n} + \sum_n \gamma_{l,n}^w s_{l,n}\frac{\mathrm{d}(1-\mathrm{ATR}_n)}{1-\mathrm{ATR}_n}$$

Similarly, I define the growth rate of the labor supply at the local labor market level by:

$$\frac{\mathrm{d}H_l}{H_l} = \alpha_l^H + \sum_n \beta_{l,n}^H s_{l,n}\frac{\mathrm{d}(1-\mathrm{MTR}_n)}{1-\mathrm{MTR}_n} + \sum_n \gamma_{l,n}^H s_{l,n}\frac{\mathrm{d}(1-\mathrm{ATR}_n)}{1-\mathrm{ATR}_n}$$

D Data and Variable Construction

D.1 Main Data

The primary dataset used in this study is the *Échantillon Démographique Permanent* (EDP), an individual-level panel that randomly selects approximately 4% of the French population based on their date of birth. More specifically, individuals born in the first four days of each quarter in a calendar year are sampled. The EDP gathers information from various data sources, including the census, matched employer-employee data (from the *DADS* database), as well as other administrative datasets like income tax returns and data from social agencies. It is important to note that the EDP collects not only individual-level variables on the sampled individuals but also individual-level variables of other household members and household-level variables. Only the individuals included in the sample have a unique identifier that persists over time, while other household members do not.

The census data provide extensive details about individuals' demographics, including their birth and death dates, places of birth and death, and gender, among other attributes. I use the census to determine individuals' ages and genders.

The employer-employee dataset is a valuable source of information, offering detailed insights into labor-related aspects such as labor earnings, the number of hours worked, contract type, occupation, and sector of employment. It also helps identify an individual's main activity and primary employing firm, particularly when an individual has multiple employment spells with different firms in a given year. In such cases, the attributes associated with the longest spell (or the one with the highest labor earnings if two spells are of equal duration) are considered the main activity and firm. I use this dataset to construct variables such as annual hours worked, the number of days worked, contract type (full-time or part-time), and hourly wage rates.

Additionally, the EDP contains supplementary data from income tax returns, encompassing individual and household income components such as labor earnings, capital income, unemployment benefits, taxes, and tax credits. This dataset also includes information about welfare benefits that individuals claim through social agencies. I use individual and household income data, along with various socio-economic characteristics, to calculate wage subsidies and disposable income for individuals. Furthermore, these data help define individuals' places of residence.

D.2 Construction of the Sample

To construct the dataset used for the empirical analysis in this paper, I follow a systematic process consisting of the following steps:

- **Step 1**: selection of the population
- **Step 2**: simulation of the tax and benefit system
- **Step 3**: construction of the estimation samples
- **Step 4**: data aggregation and binning.

The subsequent sections provide a detailed explanation of each of these steps.

D.2.1 Step 1: selection of the population

First, I apply a selection process for each year independently. For the years from 2011 to 2018, I include individuals who have filed at least one income tax return as either the primary or secondary filer. I exclude individuals who passed away during the year, those with a place of residence outside the French metropolitan area, and those aged less than 25 or more than 55.

For years prior to and including 2011, I exclude individuals who entered into marriage or a civil union within the year. This is because these individuals were required to file multiple tax returns–one for each specific marital status period–making it complicated to simulate their annual tax rates. Specifically, I categorize individuals as part of a couple if they are married or in a civil union. For the years from 2011 to 2018, I also exclude individuals who went through divorce or experienced the death of their spouse for similar reasons.

Second, I narrow down the population to include only individuals for whom I can identify a single and unique statistical household within a given year. The definition of a tax household used in income tax returns differs from the conventional statistical household definition. In particular, statistical households can encompass multiple tax households. For example, if two single occupants reside in the same dwelling, they constitute one statistical household but two tax households. To address this, I limit my sample to individuals whose tax household corresponds to their unique statistical household. To achieve this, I follow these steps: I begin by restricting the sample to statistical households with a unique combination of primary and secondary filers. I retain statistical households where being in a couple is equivalent to being married or in a civil union. This means the number of tax filers is two for individuals in couples and one for those who are single. I exclude individuals who appear in at least two different statistical households.

Third, I further narrow down the sample to statistical households for which I have information on the number of dependents. Given that my analysis focuses on salaried workers, I exclude statistical households with self-employed incomes, retirement incomes, or foreign incomes. I also exclude households where the sampled individual has an hourly wage rate below the minimum wage minus one euro if working (to account for potential measurement error at the individual level).

D.2.2 Step 2: simulation of the tax and benefit system

To compute marginal and average tax rates and generate the associated simulated instruments, I use OpenFisca, a tax and benefit simulator designed for the French tax system that is accessible online (https://fr.openfisca.org/) and implemented in Python.

Before running the simulations, I first estimate the counterfactual labor earnings for individuals who did not work in a specific year and thus reported zero labor earnings (see Section D.4 for more details).

OpenFisca requires various variables regarding income and socio-economic characteristics at both the individual and household levels. At the individual level, I provide data on marital status (single, divorced, widowed, civil union, married), labor earnings (including counterfactual earnings for those not working), unemployment insurance, retirement income, alimony payments, and the actual number of hours worked. At the household level, I use data on the number of dependents and their respective statuses, real estate incomes, capital incomes, information on received housing benefits, and the city of residence as an input.[38]

Next, I conduct separate simulations for disposable income and wage subsidies for each year, assuming full take-up of welfare benefits. To achieve this, I make two key assumptions. First, I evenly distribute annual labor earnings across each month within a year. Second, I calculate wage subsidies and welfare benefits based solely on monthly earnings. It is important to note that this is a simplification since two of the wage subsidy programs (RSA activité and Prime d'Activité) consider average earnings over the previous three months. Due to the static nature of OpenFisca's simulations, I do not account for this rule. However, this approach provides a reasonable initial approximation of wage subsidies under full benefit take-up at the annual level.

[38]Treating housing benefits as constant in the calculation of marginal and average tax rates is a strong assumption, as these benefits can partially depend on income. Unfortunately, I lack data on rent payments, which are essential for accurately computing housing benefits. Consequently, I assume that housing benefits do not significantly influence the determination of marginal and average tax rates, conditional on local labor market and socio-economic fixed effects.

I also compute gross labor earnings and gross wage rates at the individual level, which include payroll taxes. Using OpenFisca, I invert the payroll tax system to compute these measures. However, the payroll tax system is structured in a way that makes it difficult to directly compute the actual payroll taxes paid, leading to potentially noisy approximations. Specifically, I assume that individuals are employed in the private sector and are not executives.

Finally, I compute three sets of marginal and average tax rates. The first set considers the full tax and benefit system, the second set focuses solely on the wage subsidies, and the final one includes payroll taxes in addition to the full tax and benefit system.

D.2.3 Step 3: construction of the estimation samples

I focus on individuals in the sample who have a unique, consistent identifier. I retain observations where the relationship between observed net labor earnings and taxable labor earnings is consistent, as taxable labor earnings should generally exceed net earnings due to the inclusion of non-deductible social contributions. I include individuals with non-zero labor earnings meeting this condition, as well as those with zero labor earnings. All monetary values are converted to real terms, using 2011 as the base year.

The main sample is restricted to low-wage earners, defined as individuals with a pre-tax hourly wage rate below €14 per hour in the initial year t. I also construct alternative samples using thresholds of €14.50 and €€15 per hour.

To create a panel dataset, I match variables for each individual from year t to year $t + h$, including only those observed in both periods. In the baseline analysis, I set $h = 3$. The initial year t ranges from 2011 to 2015, with 2015 being the last year of earnings before the reform. This yields five time periods: 2011–2014, 2012–2015, 2013–2016, 2014–2017, and 2015–2018. Additionally, I perform analyses using two-year growth rates ($h = 2$) while maintaining the same range for the initial year t.

D.2.4 Step 4: data aggregation and binning

In the final step, I aggregate variables at the relevant level of analysis following the procedure detailed in Section 3.2. For example, tax shocks are aggregated at the socio-economic group n and time period t level, while outcomes and exposures are aggregated at the local labor market l and time period t level for the shift-share analysis in Section 5 and at the (l, n, t) level for the micro analysis in Section 6.

D.3 Additional Data

Population Census. More detailed information on the data is available at Progedo-Adisp (for instance, documentation for the 2012 version can be found here). Below is a translation of the population census sampling design.

“Municipalities with fewer than 10,000 inhabitants are surveyed once every five years on a rotating schedule. To do this, they have been divided into five groups according to specific rules that ensure each group represents the same demographic weight within each region. For municipalities with more than 10,000 inhabitants, the annual census involves a random sample of addresses, representing about 8% of the population, and is designed to be representative of the IRIS areas. After five years, the entire territory of each municipality is accounted for, and approximately 40% of the inhabitants of these municipalities are surveyed.

Thus, the frequency of data collection is quinquennial for municipalities with fewer than 10,000 inhabitants, and annual for those with 10,000 or more. The census survey is exhaustive in the first case and is carried out by sampling in the second. In reality, the process is more complex, as procedures can vary for new housing, large buildings, collective residences, mobile dwellings, and homeless populations. Each census dataset is created by combining five consecutive annual surveys, and its reference year corresponds to the median year among these five.”

I apply a selection process for each year independently. From 2011 through 2015, I include adults aged 25 to 55 (excluded), residing in metropolitan France, who are salaried employees.

D.4 Counterfactual labor earnings

To classify households into socio-economic groups accurately, I need information about their labor earnings. However, for individuals who report zero earnings in a given year, it is not possible to obtain a precise estimate of their earnings directly from the data. To address this challenge, I draw on insights from the wage subsidy literature to predict labor earnings for the portion of the sampled population that is not actively employed. It is important to note that I estimate the counterfactual labor earnings only for individuals with a unique identifier over time–that is, I exclude spouses, for whom this estimation is not applicable.

I follow a procedure similar to that of Kleven (2024). For each year separately, I begin by estimating the relationship between the log of labor earnings, $\ln(E_i)$, and a set of fixed effects, conditional on having positive earnings. For simplicity, I omit the local labor market index l, the socio-economic group index n, and the time index t. I define the following set of fixed effects:

- g: a categorical variable for gender (male/female)
- m: a categorical variable for marital status (single, divorced, widowed, civil union, married)
- r: a categorical variable for place of residence based on the French *départements* (local labor markets)
- a: a categorical variable for the age of individuals
- p: a categorical variable for the number of dependents

The Ordinary Least Squares (OLS) regression is specified as:

$$\begin{aligned}\ln(E_i) = {} & \alpha_g + \alpha_m + \alpha_r + \alpha_a + \alpha_p + \\ & \lambda_{g,m} + \lambda_{g,r} + \lambda_{g,a} + \lambda_{g,p} + \lambda_{m,a} + \lambda_{m,r} + \lambda_{m,p} + \lambda_{a,r} + \lambda_{a,p} + \lambda_{r,p} + \\ & \epsilon_i,\end{aligned} \tag{18}$$

where ϵ_i is an error term.

The estimated coefficients are then used to predict labor earnings for the non-working population: $\exp\left(\widehat{\ln(E_i)}\right)$. I follow the same procedure to predict the hourly wage rate and compute the predicted number of hours worked by dividing the predicted labor earnings by the predicted hourly wage rate.

D.5 Tax Rates

I now detail the methodology I use to compute the marginal tax rate, average tax rate and virtual income with respect to the taxable labor earnings at the individual level in any year t. For simplicity, I omit the local labor market index l and the socio-economic group index n.

I denote $T_{i,t}$ the tax function mapping incomes into taxes and benefits. Typically, $T_{i,t} = T_{i,t}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_t)$ depends on socio-economic characteristics $\boldsymbol{\Omega}_{i,t}$ and institutional parameters by $\boldsymbol{\phi}_t$, which include factors such as eligibility thresholds and parameters for the benefit schedule in year t. The important socio-economic characteristic to compute the tax rates and virtual income is the individual taxable labor earnings, $E_{i,t}$. Other factors such that other household revenues and demographic characteristics are considered constant for the computation of the individual tax rates and virtual income. For simplicity, I only express the tax function as a function of labor earnings in the remaining of this section, such that $T_{i,t} = T_{i,t}(E_{i,t}, \cdot)$.

Marginal tax rate with respect to the taxable labor earnings. The marginal tax rate is the additional increase in taxes and benefits when labor earnings vary by a small amount. We can approximate this definition by considering a small increase of €100, such that the marginal tax rate is equal to:

$$\text{MTR}_{i,t}(E_{i,t}, \cdot) = \frac{T_{i,t}(E_{i,t} + 100, \cdot) - T_{i,t}(E_{i,t}, \cdot)}{100}.$$

We can also define the marginal tax rate using the disposable income. Consider taxes and benefits can be defined as $T_{i,t}(E_{i,t}, \cdot) = C_{i,t}(E_{i,t}, \cdot) - Z_{i,t}(E_{i,t}, \cdot)$, where $C_{i,t}$ is the disposable income (after taxes and benefits) and $Z_{i,t}$ is the pre-redistribution income. The alternative formulation for the marginal tax rate is:

$$\text{MTR}_{i,t}(E_{i,t}, \cdot) = 1 - \frac{C_{i,t}(E_{i,t} + 100, \cdot) - C_{i,t}(E_{i,t}, \cdot)}{100}.$$

To compute marginal tax rates, I perform a two-step simulation of the tax system. I use the publicly available tax simulator for France Openfisca for the simulations and simulate the tax system using observed individual and household values. First, I compute taxes and the disposable income with the initial values. Second, I conduct a second simulation by adding 100 euros to taxable labor earnings, while keeping all other variables constant.

The counterfactual marginal tax rate used for the simulated instrument is computed using the same method:

$$\mathrm{MTR}_{i,t+h}(E_{i,t}, \cdot) = \frac{T_{i,t+h}(k_{t,t+h}E_{i,t} + 100, \cdot) - T_{i,t+h}(k_{t,t+h}E_{i,t}, \cdot)}{100}$$

where $e_{i,t+h}$ is the labor earnings for individuals i in year $t+h, h > 0$. All incomes, including labor earnings, are multiplied by the inflation coefficient $k_{t,t+h}$ between period t and $t+h$ based on CPI series computed by the INSEE. I apply the same procedure as before to compute the marginal tax rate with respect to the full tax and benefit system.

Average tax rate with respect to the taxable labor earnings. The average tax rate captures the difference in taxes and benefits when working versus not working. More precisely, it can be computed using the following formula:

$$\mathrm{ATR}_{i,t}(E_{i,t}, \cdot) = \frac{T_{i,t}(E_{i,t}, \cdot) - T_{i,t}(0, \cdot)}{E_{i,t}}$$

We can again use an alternative formulation using the disposable income:

$$\mathrm{ATR}_{i,t}(E_{i,t}, \cdot) = 1 - \frac{C_{i,t}(E_{i,t}, \cdot) - C_{i,t}(0, \cdot)}{E_{i,t}}$$

To compute average tax rates, I perform a two-step simulation of the tax system. I use the publicly available tax simulator for France Openfisca for the simulations and simulate the tax system using observed individual and household values. First, I compute taxes and the disposable income with the initial values. Second, I conduct a second simulation by setting taxable labor earnings to zero, while keeping all other variables constant.

The counterfactual average tax rate used for the simulated instrument is computed using the same method:

$$\mathrm{ATR}_{i,t+h}(E_{i,t}, \cdot) = \frac{T_{i,t+h}(k_{t,t+h}E_{i,t}, \cdot) - T_{i,t+h}(0, \cdot)}{k_{t,t+h}E_{i,t}}$$

Marginal tax rate with respect to gross labor earnings. I show how to compute the marginal tax rate with respect to the gross labor earnings. Gross labor earnings $\tilde{E}_{i,t}$ are inclusive of employer and employee social contributions, such that taxable labor earnings are equal to $E_{i,t} = \tilde{E}_{i,t} - T^{sc}(\tilde{E}_{i,t})$. Total taxes and benefits are equal to $T^{tot}(\tilde{E}_{i,t}, \cdot) = T^{sc}(\tilde{E}_{i,t}) + T^{inc}(E_{i,t}, \cdot)$.

The total marginal tax rate with respect to the gross labor earnings is therefore equal to:

$$\begin{aligned}
\mathrm{MTR}^{tot}_{i,t+h}(\tilde{E}_{i,t},\cdot) \equiv \frac{\partial T^{tot}(\tilde{E}_{i,t},\cdot)}{\partial \tilde{E}_{i,t}} &= \frac{\partial T^{sc}(\tilde{E}_{i,t})}{\partial \tilde{E}_{i,t}} + \frac{\partial T^{inc}(E_{i,t})}{\partial E_{i,t}}\frac{\partial E_{i,t}}{\partial \tilde{E}_{i,t}} \\
&= \mathrm{MTR}^{sc}_{i,t+h}(\tilde{E}_{i,t}) + \left[1 - \mathrm{MTR}^{sc}_{i,t+h}(\tilde{E}_{i,t},\cdot)\right]\mathrm{MTR}^{inc}_{i,t+h}(E_{i,t},\cdot),
\end{aligned}$$

where $\mathrm{MTR}^{inc}_{i,t+h}(E_{i,t},\cdot)$ is the marginal income tax rate with respect to the taxable earnings, defined above. $\mathrm{MTR}^{sc}_{i,t+h}(\tilde{E}_{i,t},\cdot)$ is the marginal social contributions tax rate defined by:

$$\begin{aligned}
\mathrm{MTR}^{sc}_{i,t+h}(\tilde{E}_{i,t}) &= \frac{\left[\tilde{E}_{i,t}(E_{i,t}+100) - (E_{i,t}+100)\right] - \left[\tilde{E}_{i,t}(E_{i,t}) - E_{i,t}\right]}{\tilde{E}_{i,t}(E_{i,t}+100) - \tilde{E}_{i,t}(E_{i,t})} \\
&= \frac{\left[\tilde{E}_{i,t}(E_{i,t}+100) - \tilde{E}_{i,t}(E_{i,t})\right] - 100}{\tilde{E}_{i,t}(E_{i,t}+100) - \tilde{E}_{i,t}(E_{i,t})} \\
&= 1 - \frac{100}{\tilde{E}_{i,t}(E_{i,t}+100) - \tilde{E}_{i,t}(E_{i,t})}
\end{aligned}$$

Average tax rate with respect to gross labor earnings. Similarly, I can define the average tax rate including social contributions using the following formula:

$$\begin{aligned}
\mathrm{ATR}^{tot}_{i,t}(\tilde{E}_{i,t},\cdot) &= \frac{\left[T^{sc}(\tilde{E}_{i,t}) + T^{inc}(E_{i,t},\cdot)\right] - \left[T^{sc}(0) + T^{inc}(0,\cdot)\right]}{\tilde{E}_{i,t}} \\
&= \frac{T^{sc}(\tilde{E}_{i,t}) + \left[T^{inc}(E_{i,t},\cdot) - T^{inc}(0,\cdot)\right]}{\tilde{E}_{i,t}} \\
&= \frac{T^{sc}(\tilde{E}_{i,t})}{\tilde{E}_{i,t}} + \frac{T^{inc}(E_{i,t},\cdot) - T^{inc}(0,\cdot)}{E_{i,t}}\frac{E_{i,t}}{\tilde{E}_{i,t}} \\
&= \frac{\tilde{E}_{i,t} - E_{i,t}}{\tilde{E}_{i,t}} + \mathrm{ATR}^{inc}_{i,t}(E_{i,t},\cdot)\frac{E_{i,t}}{\tilde{E}_{i,t}} \\
&= 1 - \frac{E_{i,t}}{\tilde{E}_{i,t}} + \mathrm{ATR}^{inc}_{i,t}(E_{i,t},\cdot)\left(1 - \left[1 - \frac{E_{i,t}}{\tilde{E}_{i,t}}\right]\right) \\
&= \mathrm{ATR}^{sc}_{i,t}(E_{i,t},\cdot) + \mathrm{ATR}^{inc}_{i,t}(E_{i,t},\cdot)(1 - \mathrm{ATR}^{sc}_{i,t}(E_{i,t},\cdot))
\end{aligned}$$