Wage and Employment Effects of Wage Subsidies*

Maxime Gravoueille

February 6, 2024

Abstract

This paper presents new evidence on the economic incidence of wage subsidies by estimating their effects on wage and employment. I examine a large 2015 national-level reform in France, which increased financial support for low-income working households. Using administrative data and a shift-share IV design, I leverage variations in reform exposure across local labor markets stemming from differences in the socio-economic composition of the local working-age population. I find that local labor markets more exposed to an increase in wage subsidies experience an increase in the growth rate of hours worked. This surge in employment is associated with a decrease in the average hourly wage growth rate. Overall, there is no significant impact on total pre-tax labor earnings growth at the local level, as the effects on wages and employment are offsetting. These results suggest a pass-through of wage subsidies to wages equal to 28% on average.

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

Keywords: Wage subsidies, wage effect, employment effect, tax incidence, shift-share IV.

---

*Maxime Gravoueille: Monash University (maxime.gravoueille@monash.edu). I am extremely grateful and indebted to Philippe Aghion and Stefanie Stantcheva for their guidance. I thank also Victor Augias, Sascha Becker, Sir Richard Blundell, Pierre Boyer, Antoine Bozio, Jeanne Commault, Olimpia Cutinelli Rendina, Léo Czajka, Quoc-Anh Do, Stefanie Fischer, Simon Gleyze, Maxence Gouleau, Moshe Hazan, Xavier Jaravel, Attila Lindner, Kaveh Majlesi, Simon Margolin, David Margolis, Antoine Mayerowitz, Daniel Prinz and Sarah Schneider-Strawczynski for their advice and comments. I thank numerous seminar and conference participants at the Institute for Fiscal Studies, Paris School of Economics, Collège de France, INSEAD, IIPF, SMYE and University of Melbourne.

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 (see Hoynes (2019) for a recent review), there is still limited evidence regarding who benefits from them between workers and employers. 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; Zurla, 2022).

This paper empirically challenges the idea that the economic incidence of wage subsidies falls entirely on workers by departing 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 compositions of the local working-age population.

Most of the recent microeconomic literature focuses on labor supply, namely workers, casting aside equilibrium effects on the labor market (e.g., Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Grogger, 2003; Hotz and Scholz, 2006; Bollinger, Gonzalez, and

Ziliak, 2009; Gelber and Mitchell, 2012; Gelber and Mitchell, 2012; Kleven, 2019; Bastian, 2020; Whitmore Schanzenbach and Strain, 2021; Chetty, Friedman, and Saez, 2013; Chetty and Saez, 2013; Agostinelli, Borghesan, and Sorrenti, 2021). 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 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 reasonable to examine the employment effect of wage subsidies, it is unable to identify the wage effect. Because they participate in the same labor market, an increase in employment from the treated group also reduces the hourly wage rate in the control group. By extension, it is also unhelpful to estimate the overall effect on labor earnings. Taking into account this channel has substantial implications in accessing 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). One needs a research design that allows for both labor supply and labor demand responses to the policy. This paper sheds a new light on this question by using a novel identification strategy and a unique reform of wage subsidies in France in 2015. 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 a shock that differs 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 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.[1] In particular, sampled individuals are followed over time, allowing me to precisely track their labor market outcomes. This unique combination of nationwide reform in a large economy with a heterogeneous population and high-quality panel data on individuals and households is ideal for studying the wage and employment effects of wage subsidies.

First, I outline a simple conceptual framework that provides the essence of the rest of the empirical analysis. I begin by building a competitive labor market model, based on Rothstein (2010), allowing for equilibrium effects in the presence of wage subsidies. The model features labor supply responses at the intensive margin and extensive margin. Each local labor market contains many agents that differ in socio-economic characteristics used for computing wage subsidies in a non-linear schedule (e.g., household income, marital status, or having 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 especially shows that an increase in labor supply at the labor market level is partly offset by a decrease in the hourly wage rate if labor demand is less than perfectly elastic.

Then, 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 channels can be recovered via labor market level regression using a shift-share instrumental variable design. This identification stems from two factors. First, the wage subsidy 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

[1] 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).

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. I construct two exposure measures that are relevant for my analysis: the hour-weighted change in the marginal tax rate and the hour-weighted change in the average tax rate due to the reform, at the local labor market level.

The validity of this research design relies on the quasi-random assignment of shocks (Borusyak, Hull, and Jaravel, 2022). Intuitively, this means that a change in wage subsidies should not have been chosen strategically, based on local labor market trends, or in a way that correlates with such trends. This assumption naturally holds in my design, as the wage subsidy schedule is set at the national level and is therefore not directly indexed to labor market characteristics. A threat to the analysis is the reverse causality between wage subsidies and labor earnings. I build on the simulated instruments literature and compute the tax rates under the assumption of no behavioral responses to the reform. To validate my research design and show that changes in wage subsidies are not correlated with other unobservable local labor market features also affecting wages and employment, I construct falsification tests based on a regression of past outcomes on current shocks.

Finally, I use my quasi-experimental research design to evaluate the effect of the 2015 French reform on wage subsidies. I find sizeable wage and employment responses with respect to the average tax rate. On the contrary, I do not find any significant responses with respect to the marginal tax rate. I find that a decrease in 10% of the average tax rate increases by 3.4% the number of hours worked and decreases by 2.8% the hourly wage rate, relative to the situation without any change in wage subsidies. Overall, I find no significant effect on pre-tax labor earnings growth at the local labor market level, as the wage effect and the employment effect are of similar magnitude. These effects suggest a pass-through of wage subsidies to wages equal to 28% on average.

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 and Liebman, 1996; Meyer and Rosenbaum, 2001; Grogger, 2003; Hotz and Scholz, 2006; Gelber and Mitchell, 2012; Bastian, 2020; Whitmore Schanzenbach and Strain, 2021). However, Kleven (2019) 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, and Saez (2013) find large and significant responses to kinks in the EITC schedule. However, Bollinger, Gonzalez, and Ziliak (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; Zurla, 2022), 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 that of Leigh (2010). He finds that an increase of 10% in the EITC decreases the hourly wage rate by 5 % for high school dropouts. However, this result is not compatible with reasonable incidence parameters for wage subsidies. 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. To do so, I combine recent advances in Bartik/shift-share IV design (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 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. By estimating wage and employment effects, I can provide the share of subsidy going to employers and workers. Rothstein (2010) investigates incidence of the EITC using a competitive partial equilibrium model for the labor market and calibrations along a range of plausible values for the labor supply and demand elasticities. Focusing on the labor market for women, he finds a fall in total earnings primarily due to a decrease in the wage rate, leading to only 70% of a dollar increase in the EITC going to low-skilled mothers. Azmat (2019) shows, in a specific context of the tax credit being paid through employers, that firms cut by 7% the wage of claimants relative to nonclaiments, which is suggestive of a negative spillover between the two groups. Zurla (2022) identifies a pass-through rate of 50% within the context of a substantial Italian EITC program at the firm-level. I discuss more the results in the context of this literature in Section 6. I show that employers are able to capture a sizeable part of wage subsidies, up to 28% 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 and Gottlieb, 2021; Ortigueira and 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, with a particular focus on the 2015 reform of wage subsidies. Section

3 presents the conceptual framework and the quasi-experimental research design based on shift-share IV. Section 4 describes the data, variables construction and provides summary statistics. Section 5 reports causal estimates at the labor market level. Section 6 discusses some mechanisms and limitations. Section 7 concludes.

2 Institutional Background

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, not only by increasing financial incentives for working but also by minimizing the reduction in welfare benefits (transfers not contingent on employment) when individuals return to work. 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. It features both an increasing phase-in and a decreasing phase-out as a function of earnings. The following formula summarizes the level of benefits individuals are eligible for based on their socio-economic characteristics:

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

where $B_{i,t}$ is the amount of benefit for individual i in year t, based on socio-economic characteristics $\boldsymbol{\Omega}_{i,t} = \{w_i h_i, \boldsymbol{R}_{i,t}, \boldsymbol{D}_{i,t}\}$ 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).

Timeline and implications of the reform. Before the 2015 reform, and for incomes earned prior to 2016, two wage subsidy programs were in place. First, a tax credit known as *Prime Pour L'emploi*, which individuals could claim through the income tax system on an annual basis. The 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, as individuals eligible for it automatically received it from the tax administration. Second, an in-work benefit program known as *Revenu de Solidarité Activité*, provided to individuals through social programs on a monthly basis. This program targeted a lower segment of the earnings distribution compared to 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 systems.

Following the 2015 reform and for incomes earned from 2016 onwards, the income tax credit and the in-work benefit were merged into a single and unified in-work benefit known as the *Prime d'Activité*. The goal of this reform was to simplify the system by creating a single, easily accessible in-work benefit, which individuals could receive through social programs on a monthly basis.[2] In contrast to the primary tax credit available before 2015 (inclusive), this new benefit is not automatically distributed to eligible individuals. As a result, the take-up rate has significantly decreased, although it has remained relatively high (73% in 2016, as reported in DREES and CNAF (2017)). The timing of the reform effectively minimizes anticipatory effects, given that the reform was passed in late August 2015 and came into effect in January 2016. To support this assertion, Figure B.1 and Figure B.2 display the Google Trends index for each wage subsidy program over time. The search index

[2]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.

for the post-reform wage subsidy program remains flat and close to zero before December 2015, but it exhibits a sharp increase afterward. This pattern provides further evidence that individuals were likely unaware of the reform until its actual implementation.

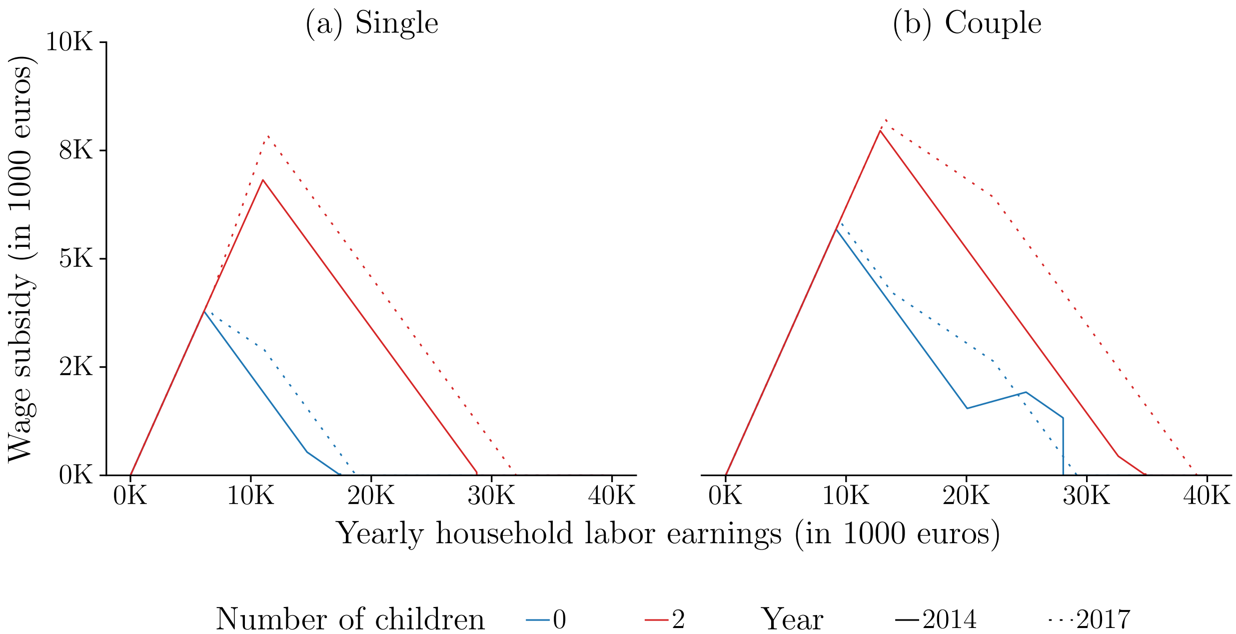
Figure 1 illustrates the wage subsidy schedule before and after the reform, for years 2014 and 2017 respectively. I plot the amount of wage subsidy for households with various socio-economic characteristics, from a simple simulation where labor earnings are the sole source of income and under the assumption that labor earnings are evenly distributed among partners in a couple. Both panels, panel (a) for single individuals and panel (b) for couples, reveal three facts. First, the wage subsidy schedule exhibits non-linearity, featuring salient eligibility thresholds, a phase-in segment, and a phase-out segment. Second, the wage subsidy schedule has considerable differences depending on an individual's socio-economic characteristics. Finally, the reform has introduced substantial variation 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.

2.2 French Labor Market

The French labor market has been characterized by high participation rates among its population since the early 1990s, both for men and women. Figure B.3 shows the labor force participation rates for prime-age workers for France, the United Kingdom and the United States, by gender and over time. Panel (a) displays participation rates for men, ranging from 90% to 95%, with similar levels observed in France, the United Kingdom, and the United States. Panel (b) shows that women have witnessed a significant increase in labor force participation in France and the United Kingdom, reaching 80% to 85% by 2019. In contrast, the United States has experienced stagnation in women's participation, hovering around 75%.

The disparities in labor market outcomes between genders become even clearer for part-time employment. Figure B.4 illustrates the proportion of employed workers in part-time, by

Figure 1: Examples of the French wage subsidy schedule



Notes: The figure plots the wage subsidy amount that a household is eligible for based on its yearly household income per adult, considering various household characteristics and different years. 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 2 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 tax 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.

gender and over time. Panel (a) shows that men are mostly engaged in full-time work, while panel (b) shows that women are more likely to work part-time. Notably, there are substantial differences in the share of women in part-time employment among these countries, with the United States at 10%, France at 20%, and the United Kingdom at 30% in 2019.

One potential explanation for these variations is the cost of childcare. Figure B.5 shows the childcare costs for households with two children, as a percentage of net household income, for both single parents (panel (a)) and couples (panel (b)). Childcare costs in France are relatively low, approximately 10% in both scenarios, while they are significantly higher in the United States, reaching around 40% for single parents and 20% for married couples. The United Kingdom falls in between as an intermediate case.

3 Conceptual Framework and Quasi-Experimental Research Design

This section introduces the empirical methodology employed in this paper. It begins with a stylized model based on Rothstein (2010), which provides valuable reduced-form formulas for understanding how wage and employment effects can be estimated through labor market-level regressions. While the model relies on restrictive assumptions that are not necessary for the empirical analysis, it is a helpful conceptual framework. Then, I show how the quasi-experimental shift-share instrumental variable design from Borusyak, Hull, and Jaravel (2022) can be applied to establish causal estimates.

3.1 A Simple Model of Wage Subsidies with Equilibrium Effects

3.1.1 Setup

I consider a static economic framework with a population of individuals from distinct labor markets, denoted as $m = 1, \ldots, M$. In the context of this paper, these markets represent various combinations of geographical locations or local labor markets. Labor is the only input factor used to produce, and both the output and labor markets operate under perfect competition.

Production. A representative firm produces Y with constant elasticity of substitution between the different labor markets. The firm's optimal labor choices solve the cost minimization problem:

$$\min_{\{w_k\}_k} \sum_{k=1}^{M} w_k L_k \quad \text{such that} \quad \left(\sum_{k=1}^{M} \beta_k L_k^{\frac{1+\varepsilon^d}{\varepsilon^d}} \right)^{\frac{\varepsilon^d}{1+\varepsilon^d}} \geq Y$$

with w_k and L_k the wage rate and labor demand in labor market k. Labor demand for local labor market m is $L_m = \varphi(\boldsymbol{w}) \cdot \beta_m^{-\varepsilon^d} \cdot w_m^{\varepsilon^d}$, with $\varphi(\boldsymbol{w})$ an aggregate demand component common to all labor markets. The change in wage rate for labor market m is:

$$\frac{\mathrm{d}w_m}{w_m} = \frac{1}{\varepsilon^d} \cdot \frac{\mathrm{d}\varphi(\boldsymbol{w})}{\varphi(\boldsymbol{w})} + \frac{1}{\varepsilon^d} \cdot \frac{\mathrm{d}L_m}{L_m} \tag{1}$$

Household preferences. Within each labor market denoted as m, individuals are categorized into socio-economic groups, indexed by g. In the context of this paper, these groups are defined by various factors, such as individual labor earnings, total household income, marital status, or the number of children in the household. These factors collectively determine the level of taxes and benefits, such that these socio-economic groups can be seen as measures of the treatment intensity resulting from subsidy reforms.

Individuals who want to participate in the labor market incur an entry cost $q_{m,g}$. Once they decide to participate, they then choose the number of hours worked, denoted as $h_{m,g}$. The representative individual's objective is to maximize their utility, denoted as $U(c_{m,g}, h_{m,g}) = v(c_{m,g}, h_{m,g}) - q_{m,g} \cdot 1\left[h_{m,g} > 0\right]$, subject to the budget constraint $c_{m,g} = w_m h_{m,g} - T_{m,g}(w_m h_{m,g})$. Here, $c_{m,g}$ represents disposable income and $T_{m,g}(w_m h_{m,g})$ represents taxes and benefits.

The optimal number of hours worked is equal to $h_{m,g} = h(w_m(1 - \mathrm{MTR}_{m,g}))$, which depends on the wage rate and the marginal tax rate. The optimal participation rate is defined by $P_{m,g} = P(w_m h_{m,g}(1 - \mathrm{ATR}_{m,g}))$, which factors in the wage rate, hours worked, and the average tax rate. The first condition addresses the intensive margin, where the optimal hours worked depend positively on the wage rate but negatively on the marginal tax rate. The second condition pertains to the extensive margin, where the optimal participation rate depends positively on the wage rate and hours worked, but negatively on the average tax rate, reflecting the difference in taxes and subsidies between participation and non-participation scenarios.

Labour supply at the labor market level. In a given labor market, a treatment group has $N_{m,g}$ potential workers. These individuals can adjust their labor supply both at the intensive and extensive margin. Thus, the labor supply for the group denoted as m, g is $L_{m,g} = N_{m,g}P_{m,g}h_{m,g}$, while the overall labor supply in labor market m is given by $L_m = \sum_g L_{m,g}$. The growth rate in labor supply at the market level is then:

$$\frac{\mathrm{d}L_m}{L_m} = \sum_g \frac{L_{m,g}}{L_m}\frac{\mathrm{d}P_{m,g}}{P_{m,g}} + \sum_g \frac{L_{m,g}}{L_m}\frac{\mathrm{d}h_{m,g}}{h_{m,g}} \tag{2}$$

$$\frac{\mathrm{d}h_{m,g}}{h_{m,g}} = \varepsilon^c\left[\frac{\mathrm{d}w_m}{w_m} + \frac{\mathrm{d}(1-\mathrm{MTR}_{m,g})}{1-\mathrm{MTR}_{m,g}}\right] \tag{3}$$

$$\frac{\mathrm{d}P_{m,g}}{P_{m,g}} = \varepsilon^p\left[\frac{\mathrm{d}w_m}{w_m} + \frac{\mathrm{d}h_{m,g}}{h_{m,g}} + \frac{\mathrm{d}(1-\mathrm{ATR}_{m,g})}{1-\mathrm{ATR}_{m,g}}\right] \tag{4}$$

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. Under the assumption of no wage effect ($\mathrm{d}w_m/w_m = 0$), we have the classic employment effect of a change in taxes, assuming no equilibrium effects.

3.1.2 Wage and employment effects

I define the market exposure to changes in the marginal tax rates and average tax rates using the following weighted averages:

$$X_m^{1-MTR} = \sum_g \frac{L_{m,g}}{L_m}\frac{\mathrm{d}(1-\mathrm{MTR}_{m,g})}{1-\mathrm{MTR}_{m,g}} \quad \text{and} \quad X_m^{1-ATR} = \sum_g \frac{L_{m,g}}{L_m}\frac{\mathrm{d}(1-\mathrm{ATR}_{m,g})}{1-\mathrm{ATR}_{m,g}}$$

Combining equations (1)-(4), the wage and employment effects at the market level are functions of these two market exposures:

$$\frac{\mathrm{d}w_m}{w_m} = \alpha^w + \beta^w \cdot X_m^{1-MTR} + \gamma^w \cdot X_m^{1-ATR} \quad \text{and} \quad \frac{\mathrm{d}L_m}{L_m} = \alpha^L + \beta^L \cdot X_m^{1-MTR} + \gamma^L \cdot X_m^{1-ATR}$$

where β^w, β^L, γ^w, and γ^L represent the labor market-level elasticities of interest, which themselves depend on a set of structural parameters:

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

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

The labor market level equations are of particular interest for two main reasons. First, they illustrate how the impact of a change in wage subsidies on employment and wage rate growth can be directly estimated using labor market-level regressions. The overall response for each of these variables depends on the sum of the growth rate of the net-of-tax rate (one minus the marginal tax rate) for each treatment group, weighted by the initial number of hours in these groups, and on the sum of the growth rate of the participation tax rate (one minus the average tax rate) for each treatment group, also weighted by the initial number of hours in these groups. In subsection 3.2, I demonstrate that this analysis is akin to a shift-share research design when the wage subsidy schedule is established at the national level. The equivalence arises when $(1 - \mathrm{MTR}_{m,g}) = (1 - \mathrm{MTR}_g)$ and $(1 - \mathrm{ATR}_{m,g}) = (1 - \mathrm{ATR}_g), \forall m$.

Second, the magnitude of the response to these wage subsidy shocks depends on the magnitude of the demand elasticity ε^d, the participation elasticity ε^p, and the compensated elasticity of labor supply ε^c. When $\varepsilon^d \to -\infty$, the labor demand becomes completely elastic, leading to no wage effect. Labor market-level regressions estimate a mixture of these elasticities.

3.2 Quasi-Experimental Research Design

In this section, I demonstrate that variations in the intensity of treatment 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, exogenous shocks to wage subsidies defined at the national level.

3.2.1 Setting

Consider panel data containing observations on individuals, indexed as i, across two consecutive time periods, denoted as t and $t+h$, $h>0$. These individuals live in a specific local labor market denoted as m and potentially belong to various treatment groups, indexed by g, which determine their entitlement to tax and benefit levels in year t. These treatment groups are determined based on factors such as individual labor earnings, total household labor earnings, marital status, and the number of children. Importantly, the assignment to treatment group g is independent of the characteristics of the local labor market, as the wage subsidy program operates nationwide.

3.2.2 Treatment intensity definition

I begin by quantifying the variation in the net-of-tax rate (defined as one minus the marginal tax rate) and the participation tax rate (defined as one minus the average tax rate) for different treatment groups within a given labor market. The shock, denoted as $\theta_{m,g,t} \in \{\Delta\ln(1-\mathrm{MTR}_{m,g,t}), \Delta\ln(1-\mathrm{ATR}_{m,g,t})\}$ is calculated as a weighted average of individual-level shocks:

$$\theta_{m,g,t} = \sum_i \frac{h_{i,m,g,t}}{L_{m,g,t}} \times \theta_{i,m,g,t}$$

Here, $h_{i,m,g,t}/L_{m,g,t}$ represents the proportion of hours worked by individual i out of the total hours worked in labor market $\times$ treatment group. For example, the net-of-tax rate shock, $\Delta\ln(1-\mathrm{MTR}_{m,g,t})$, is computed as $\Delta\ln(1-\mathrm{MTR}_{m,g,t}) = \sum_i (h_{i,m,g,t}/L_{m,g,t}) \times \Delta\ln(1-\mathrm{MTR}_{i,m,g,t})$.

Assumption 1. *Treatment intensity varies among the different g groups but is not specific to labor market m, such that $\theta_{m,g,t}$ is a noisy version of the underlying latent shock $\theta_{g,t}$.*

$$\theta_{m,g,t} = \theta_{g,t} + \nu_{m,g,t}$$

where $\nu_{m,g,t}$ is an estimation error, and $\theta_{g,t}$ is the nationwide shock. Importantly, the wage subsidy schedule is determined at the national level, ensuring that the shock associated with each initial treatment group g is not correlated with specific labor market characteristics by design. For example, the net-of-tax rate shock, $\Delta \ln(1 - \mathrm{MTR}_{g,t})$, is computed as $\Delta \ln(1 - \mathrm{MTR}_{g,t}) = \sum_i (h_{i,m,g,t}/L_{g,t}) \times \Delta \ln(1 - \mathrm{MTR}_{i,m,g,t})$, with $L_{g,t} = \sum_{i,m} h_{i,m,g,t}$. [3]

Then, I define the labor market treatment intensity. The proportion of individuals in treatment group g within labor market m is $S_{m,g,t} = L_{m,g,t}/L_{m,t}$. This proportion varies across local labor markets due to differences in their socio-economic composition. 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:

$$X^{\theta}_{m,t} = \sum_g S_{m,g,t} \times \theta_{g,t} \tag{5}$$

This treatment variable quantifies the labor market's exposure to nationwide shocks in taxes and benefits. For instance, $X^{1-MTR}_{m,t} = \sum_g S_{m,g,t} \cdot \Delta \ln(1 - \mathrm{MTR}_{g,t})$ represents the hours-weighted growth rate in the net-of-tax rate for labor market m in the initial year t. Similarly, $X^{1-ATR}_{m,t} = \sum_g S_{m,g,t} \cdot \Delta \ln(1 - \mathrm{ATR}_{g,t})$ represents the hours-weighted growth rate in the participation tax rate for labor market m in the initial year t.[4]

Instruments. A substantial body of literature has highlighted challenges that arise when using Equation 5 directly as a treatment variable. This is because individuals adjust their labor earnings, either by altering the number of hours worked or the wage rate, in response to changes in taxes and benefits. Consequently, taxes and benefits become a direct function of labor earnings, with reverse causality as a threat to identification.

[3] For individuals who are not participating 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 treatment group. As a result, there are no substantial differences in the tax shocks for this group, given the construction of these estimates.

[4] I also report results using an alternative definition of the labor market level variables, with cross-sectional weights. The procedure is described in detail in subsection C.3.

To address this issue, I draw upon the simulated instruments literature by calculating tax rates under the assumption of no behavioral responses to the reform (e.g. Auten and Carroll, 1999; Moffitt and Wilhelm, 2000; Gruber and Saez, 2002; Kopczuk, 2005). For example, the corresponding simulated change in net-of-tax rate is:

$$\Delta^{sim} \ln(1 - \text{MTR}_{i,m,g,t}) = \ln \left[\frac{1 - \text{MTR}_{i,m,g,t+h}(\Omega_{i,m,g,t})}{1 - \text{MTR}_{i,m,g,t}(\Omega_{i,m,g,t})} \right]$$

where $\Omega_{i,m,g,t}$ encompasses individuals' characteristics in the initial year t. These characteristics include, for instance, an individual's labor earnings, other household income, and relevant household demographic information. In Section 4, I provide further details on how simulated tax rates are computed from the data. Intuitively, this method constructs counterfactual tax rates by simulating the scenario in which individual's responses to the reform are switched off, such that $\Delta^{sim} \ln(1 - \text{MTR}_{i,m,g,t})$ represents the mechanical change in the net-of-tax rate. Importantly, this change is exogenous to potential changes in the wage rate and the number of hours worked.

Finally, I follow the same procedure as in the previous paragraph to construct instruments at the labor market level:

$$Z^{\theta}_{m,t} = \sum_{g} S_{m,g,t} \times \theta^{sim}_{g,t}$$

3.2.3 Specification

I estimate a linear regression model with the outcome variable $Y_{m,t}$ and the treatment variables $X^{\theta}_{m,t}$. In this paper, I consider three sets of outcomes at the local labor market level: the change in the total number of hours worked, $\Delta \ln(L_{m,t})$, the change in the average hourly wage rate, $\Delta \ln(w_{m,t})$, and the change in total earnings, $\Delta \ln(w_{m,t} L_{m,t})$, all observed between time periods t and $t + h$. More specifically, I estimate the following model using a two-stage least squares (2SLS) approach:

$$Y_{m,t} = \beta \cdot X^{1-MTR}_{m,t} + \gamma \cdot X^{1-ATR}_{m,t} + \Lambda_{m,t} + \epsilon_{m,t}$$

The coefficients of interest are β and γ, which respectively represent the causal effects of changes in the labor market-level net-of-tax and participation tax rates. These effects are conditional on a set of time-varying control variables $\Lambda_{m,t}$. I instrument $X_{m,t}^{1-MTR}$ with $Z_{m,t}^{1-MTR}$ and $X_{m,t}^{1-ATR}$ with $Z_{m,t}^{1-ATR}$.

Following the approach outlined by Borusyak, Hull, and Jaravel (2022), I define the equivalent shock-level IV regression, which is weighted by $S_{g,t} = \sum_m S_{m,g,t}$. This is the baseline regression for the remainder of the paper.

$$\tilde{Y}_{g,t} = \beta \cdot \tilde{X}_{g,t}^{1-MTR} + \gamma \cdot \tilde{X}_{g,t}^{1-ATR} + \tilde{\Lambda}_{g,t} + \tilde{\epsilon}_{g,t} \tag{6}$$

where $\tilde{v}_{g,t} = (\sum_m S_{m,g,t} v_{m,t})/(\sum_m S_{m,g,t})$. This shock-level formulation will prove particularly useful to discuss the source of identification. Regressions include labor market and year fixed-effects, a set of fixed-effects related to the treatment group, as well as controls for socio-economic characteristics in the initial period.

3.2.4 Identification

My instruments combine two key features. First, exposure shares that are determined by the specific socio-economic composition of a local labor market. Second, shocks resulting from changes in the national tax and benefit schedule. The literature on shift-share (or Bartik) instruments has highlighted two potential sources of identification within this research design. One approach considers the exposure shares as exogenous (Goldsmith-Pinkham, Sorkin, and Swift, 2020), while the other assumes that the shocks are quasi-randomly assigned (Borusyak, Hull, and Jaravel, 2022). In this paper, I argue that my quasi-experimental research design falls in the second category.

Assumption 2. *(Conditional quasi-random shock assignment).*

$$\mathbb{E}[\theta_{g,t}^{sim} | \tilde{\epsilon}_{g,t}, \tilde{\Lambda}_{g,t}, S_{g,t}] = \tilde{\Lambda}'_{g,t} \cdot \mu$$

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

Assumption 3. *(Many uncorrelated shock residuals).*

$$\begin{cases} \mathbb{E}\left[\sum_g \sum_t S_{g,t}^2\right] \to 0 \\ \mathbb{C}ov(\theta_{(g,t)}^{sim}, \theta_{(g,t)'}^{sim} | \tilde{\epsilon}_{g,t}, \tilde{\Lambda}_{g,t}, S_{g,t}) = 0, \forall((g,t),(g,t)') \text{ with } (g,t) \neq (g,t)' \end{cases}$$

The first part provides an intuitive measure of the effective sample size: shocks should not be concentrated in a small number of treatment groups. This is equivalent to saying that as the number of observations increases, the largest importance weight in the regression, denoted as $S_{g,t}$, becomes vanishingly small. The second part asserts that the shocks are mutually uncorrelated, given the unobservables and $S_{g,t}$.

Finally, the instruments must satisfy the relevance condition, signifying that they have sufficient statistical power.

Assumption 4. *(Relevance condition).*

$$\mathbb{E}[\tilde{X}_{g,t}^{\theta} \cdot \theta_{g,t}^{sim} | \tilde{\Lambda}_{g,t}, S_{g,t}] \neq 0$$

This condition can be verified by examining the first-stage F-statistic. More generally, $\theta_{g,t}^{sim}$ qualifies as a strong instrument since it solely relies on individual characteristics from the initial period to predict the changes in shocks that would have occurred had individuals not changed their behavior.

Robustness tests. So far, I have discussed why assumptions 2 and 3 are likely to be valid in the context of this paper. The core aspect of my shift-share IV research design relies on the ability to isolate labor supply shocks stemming from a plausibly exogenous reform in wage subsidies. However, concerns may arise regarding year-specific unobservable shocks that are correlated with labor demand, potentially affecting labor market outcomes and introducing bias into my estimates. To ensure the robustness of the empirical strategy, I implement several robustness checks.

First, I construct falsification tests by regressing lagged outcome variables on current shocks. This placebo regression checks whether past outcomes are correlated with current changes in wage subsidies. If assumption 2 is valid, the coefficients are expected to be statistically insignificant. I also investigate alternative regression specifications to check that the results are robust to different model choices.

Second, I directly test assumption 3 by computing the inverse Herfindahl index, denoted as $1/\sum_{g,t} S_{g,t}^2$. Borusyak, Hull, and Jaravel (2022) demonstrate that the shock-level estimation remains robust even with an effective sample size as low as 20.

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 treatment group effects are plausible in my context. Borusyak, Hull, and Jaravel (2022) and Borusyak and Hull (2023) 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 are essential for this interpretation.[5]

4 Data, Variables Construction and Summary Statistics

In this section, I provide a brief overview of the data, the methodology for constructing labor market variables, and present key summary statistics. Additional details about the data and the construction of the variables are available in Appendix C.

4.1 Data

Data. The main data source is the *Echantillon Démographique Permanent* (EDP for short), a large individual-level panel covering approximately 4% of the French population, randomly sampled.[6] It is a rich data source linking several administrative datasets and the census.

In this paper, 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.[7] Unfortunately, a unique firm identifier is not available in this dataset. Second, I use data on individual

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

[6] Before 2008, it represented 1% of the French population, specifically individuals born during the first 4 days of October. Since 2008, the population scope has been expanded to include individuals born during the first 4 days of January, April, July, and October.

[7] 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).

and household incomes derived from income tax returns. This includes information on labor earnings, capital income, unemployment benefits, taxes, and tax credits. Additionally, I have access to details regarding welfare benefits claimed by individuals through social agencies.

Sample. I focus my interest on the population of working-age individuals, specifically those aged between 25 and 55 in a given year, residing in the French metropolitan area during the period spanning from 2011 to 2017. This demographic restriction ensures that I am capturing a population who is plausibly in the labor force, and not individuals engaged in education or retired. I also limit my sample to individuals for whom I can accurately identify the tax household. This includes single individuals living independently, as well as couples cohabiting within a marriage or civil union. This restriction is necessary because the French redistribution system factors in household characteristics such as marital status and the number of dependents. Thus, I can compute taxes and benefits with more precision.

Other data. I complement the main data with the Labor Force Survey from 2011 to 2017, which is a repeated cross-sectional dataset featuring a large number of individuals (90,000 respondents per quarter). This dataset provides detailed information on commuting patterns, including individuals' places of residence and places of work.

4.2 Variable Construction

Labor market definition. To identify the wage and employment effects of wage subsidies, the quasi-experimental research design requires distinct labor markets. In practice, as noted by Hamermesh (1996) and Rothstein (2010), it entails labor markets within which workers are substitute, and closed to some extent. I adopt a simple decomposition based on individuals' geographic residence and their initial hourly wage rates.

I start by selecting individuals who are low-wage earners if their pre-tax hourly wage falls below 14 euros per hour.[8] This condition restricts the population to individuals who

[8] This threshold is chosen based on data from INSEE, where the average hourly wage for full-time workers

are substitute in the labor market to some degree. For individuals who are not employed, I construct their respective counterfactual groups by predicting their hypothetical hourly wage rates using their socio-economic characteristics. More details are available in Appendix in subsection C.3. Next, I categorize individuals based on their geographic residence, segmenting the population by *départements*, which are administrative divisions in France comprising 101 geographical areas. Due to data limitations, my focus narrows down to 94 metropolitan areas.[9] This decomposition maximizes the number of observations within each location while preserving variations in labor market characteristics necessary for the implementation of the identification strategy.

How closed are local labor markets? Figure B.6 presents two distributions illustrating the level of interdependence among local labor markets. First, in panel (a), I plot the number of units (defined as the local labor markets and year interaction) based on the percentage of individuals residing in the same labor market between t and $t + 2$, using the main sample of analysis. Residential mobility is very limited, with a mean and median of 97% remaining in the same location over time. The first and third quartiles are equal to 97% and 98%, respectively. Second, panel (b) uses census data to determine the percentage of individuals who work in the same local labor market where they live in a given year. Once again, most individuals commute within their respective local labor markets, with a mean of 81% and a median of 89%. The first and third quartiles are equal to 80% and 93%, indicating a negatively skewed distribution. Estimates from the census 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 relatively insulated, and the limited potential for spillovers across them does not pose a threat to the identification strategy.

Labor market outcomes. The first set of variables for the analysis involves the changes in wage and employment measured at the labor market level. To derive these measures, I

is 14.15 euros.

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

restrict my sample to individuals who are observed in both year t and year $t+h$. Additionally, I categorize individuals into local labor markets based on their residence in the initial period to avoid any composition effects that may introduce bias into my measurements. At the individual-year level, I observe the number of hours worked from the employer-employee matched data, as well as data on taxable labor earnings from tax returns.[10] When constructing the outcome variables, hours worked are winsorized at the upper 99th percentile for each year, the hourly wage rate is winsorized at both the lower 1st percentile and upper 99th percentile for each year, and the labor earnings are calculated as the product of these two winsorized variables. All monetary outcomes are in real terms, with a base year of 2011.

First, I define the change in employment as the log-growth rate of the total number of hours worked in a specific labor market (omitting treatment group index g for simplicity), denoted as $\Delta \ln(L_{m,t}) = \sum_i h_{i,m,t}$, where $h_{i,m,t}$ represents the number of hours worked by individual i. Second, I construct a measure of the wage rate by calculating the hours-weighted wage rate for a given labor market in a given year as $w_{m,t} = (\sum_i w_{i,m,t} h_{i,m,t})/(\sum_i h_{i,m,t})$, where $w_{i,m,t}$ is the hourly wage rate of individual i. Then, I compute the log-growth rate of the total number of hours worked in the same labor market, denoted as $\Delta \ln(w_{m,t})$. Finally, I consider a measure of change in total earnings as the sum of the wage and employment log-growth rates $\Delta \ln(w_{m,t} L_{m,t}) = \Delta \ln(w_{m,t}) + \Delta \ln(L_{m,t})$.

Treatment groups. In subsection 2.1, 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. To construct treatment groups, I employ an approach based on the interaction between categories of household labor earnings, a binary indicator for couples, and a binary indicator for individuals with children.

I construct an equalized measure of household income, which is computed as the sum of household-level labor earnings. In cases where individuals are part of a couple, this

[10] It excludes employer social contributions and most employee social contributions.

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. Then, I split this measure into bins of 1000 euros, ranging from 0 to 30000 euros (with the final bin contains all individuals whose income is above this threshold).

Tax rates. Although taxes and benefits are available in the main dataset, marginal and average tax rates are not. To fill this gap, I use a publicly available tax simulator for France[11] to generate these rates. To account for the impact of an increase in wage subsidies, I compute the marginal and average tax rates for individual i in year t (omitting labor market index m and treatment group index g for simplicity), under the assumption of a full take-up of taxes and benefits. Consequently, my findings should be interpreted as intent-to-treat effects. I derive the marginal tax rates $\mathrm{MTR}_{i,t}$ and the average tax rate $\mathrm{ATR}_{i,t}$ using the full tax and benefit system (details provided in subsection C.3) to account for the fact that changes in labor market participation and earnings might also affect the eligibility and amount received from other programs.

Then, I compute the individual level log-growth rate for the marginal and average tax rates between year t and year $t+h$, $h>0$:

$$\Delta \ln(1-\mathrm{MTR}_{i,t}) = \ln\left[\frac{1-\mathrm{MTR}_{i,t+h}(\boldsymbol{\Omega}_{i,t+h}, \boldsymbol{\phi}_{t+h})}{1-\mathrm{MTR}_{i,t}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t})}\right]$$
$$\Delta \ln(1-\mathrm{ATR}_{i,t}) = \ln\left[\frac{1-\mathrm{ATR}_{i,t+h}(\boldsymbol{\Omega}_{i,t+h}, \boldsymbol{\phi}_{t+h})}{1-\mathrm{ATR}_{i,t}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t})}\right]$$

where, following notation from Section 2, I denote socio-economic characteristics by $\boldsymbol{\Omega}_{i,t} = \{w_i h_i, \boldsymbol{R}_{i,t}, \boldsymbol{D}_{i,t}\}$ and institutional parameters by $\boldsymbol{\phi}_t$, which include factors such as eligibility thresholds and parameters for the benefit schedule in year t. 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

[11] Openfisca is available at https://fr.openfisca.org/.

or marital status, for example). Both individual-level observed and simulated tax shocks are winsorized at the bottom 5% and top 5% for each year.

I also construct the simulated instruments for the marginal tax rate. I inflate labor earnings and other household revenues by CPI evolution between t and $t+h$:

$$\Delta^{sim} \ln(1 - \mathrm{MTR}_{i,t}) = \ln \left[\frac{1 - \mathrm{MTR}_{i,t+h}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t+h})}{1 - \mathrm{MTR}_{i,t}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t})} \right]$$
$$\Delta^{sim} \ln(1 - \mathrm{ATR}_{i,t}) = \ln \left[\frac{1 - \mathrm{ATR}_{i,t+h}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t+h})}{1 - \mathrm{ATR}_{i,t}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\phi}_{t})} \right]$$

Finally, I construct the market level treatment variables and corresponding instruments using the methodology presented in subsection 3.2. Note that the individuals are split into labor markets and treatment groups based on their characteristics in the initial year t.

4.3 Summary Statistics

Local labor markets. Table 1 provides a summary of the distribution of key outcomes and socio-economic variables at the local labor market level for the period spanning from 2011 to 2017. All variables are weighted by the share of the local labor market in the national population in the initial year, denoted as t. Panel (a) shows the two-year log-growth rates of total labor earnings, the total number of hours worked, and the average hourly wage rate. On average, labor earnings exhibit positive growth (mean = 4.7%, sd = 1.5%), primarily driven by the positive growth rate in the average hourly wage rate (mean = 5.6%, sd = 1.2%).

To gain perspective on the magnitude of these variations, panel (b) presents a set of socio-economic variables in the initial year. The average labor earnings amount to €14,667 (sd = €998), with an average hourly wage rate of €9.10 (sd = €0.50), and an average number of hours worked equal to 1,370 (sd = 88). In 2011, the annual number of hours for those working full-time amounted to 1,607, considering a minimum wage of approximately

€12,888.[12] On average, a significant portion of the population of interest 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 below €9 (mean = 19%, sd = 3%).

Table 1: Local labor markets summary statistics

	Mean	Standard deviation	p5	Median	p95
(a) Outcomes: log-growth rates between t and $t+2$					
Δ ln(labor earnings)	0.047	0.015	0.022	0.048	0.070
Δ ln(hours)	-0.009	0.014	-0.031	-0.009	0.013
Δ ln(wage)	0.056	0.012	0.041	0.055	0.075
(b) Socio-economic variables in t					
Mean labor earnings (in euros)	14,667	998	12,856	14,788	16,291
Mean hours worked	1,370	88	1,213	1,380	1,512
Mean hourly wage (in euros)	9.10	0.50	8.30	9.15	9.75
Prop. working full year	70%	5%	61%	70%	78%
Prop. with full-time contract	67%	5%	59%	67%	74%
Prop. close to MW	19%	3%	15%	19%	23%
(c) Sample size					
Local labor markets	94	94	94	94	94
Periods	5	5	5	5	5
Local labor markets $\times$ periods	470	470	470	470	470

Notes: This table summarizes the distribution of the key outcomes (panel (a)) and socio-economic variables (panel (b)) for base year t between 2011 and 2015. Panel (c) also reports summary statistics for the sample size. Close to the minimum wage is defined as having a hourly wage rate below €9. All statistics are weighted by the share of the local labor market in the national population in the initial period.

Shocks due to the reform. I continue with a brief description of the reform's effect on the change in participation and net-of-tax rates across treatment groups at the national level. In

[12] 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: https://www.insee.fr/fr/statistiques/serie/000879878.

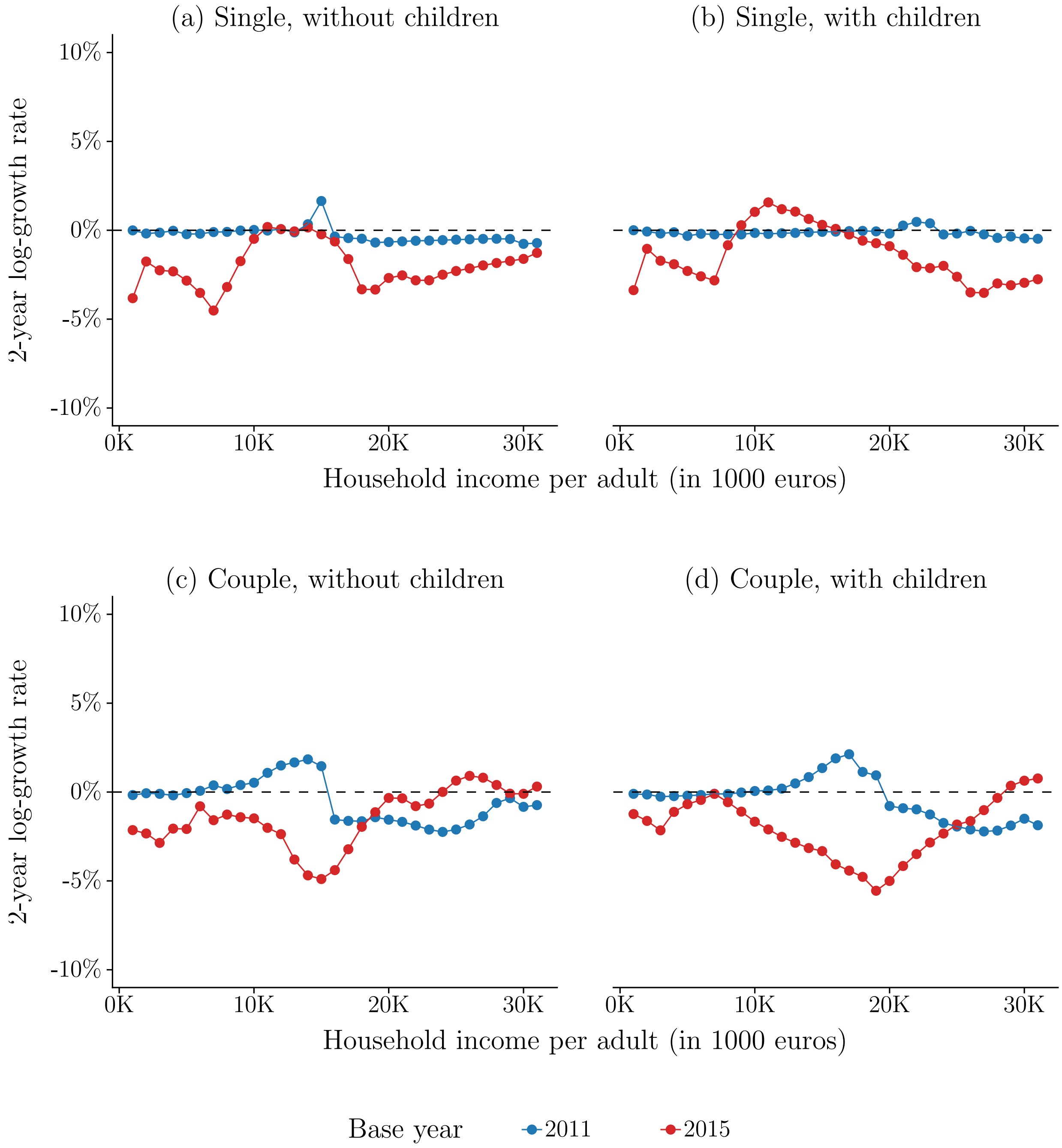
Figure 2, the 2-year log-growth of the simulated participation tax rate for different treatment groups is plotted, comparing the base year 2011 (a reform period) to 2015 (a post-reform period). During the pre-reform period, the change in the participation tax rate remains close to 0 and fairly consistent across all groups. In contrast, there is substantial variation in the participation tax rate during the reform period. These changes are particularly significant for households in the lower part of the labor earnings distribution, as they are more exposed to wage subsidies. Figure 3 presents a similar analysis for the 2-year log-growth of the simulated net-of-tax rate across different treatment groups. Once again, the changes are particularly notable for households in the lower segment of the labor earnings distribution.[13]

One potential concern about this measure is that the change in the wage subsidy schedule may not necessarily translate into the total change in taxes and benefits, implying a weak correlation between the two measures. To address this concern, I present the same plots as previously shown in Figure B.7 and Figure B.8, but this time focusing solely on the wage subsidy (weighted by the initial share of the wage subsidy in total taxes and benefits). The distribution of shocks exhibits a similar shape to the baseline plots, suggesting that differences in the change in participation and net-of-tax rates across treatment groups, when considering the full tax and benefit system, are primarily driven by changes in the wage subsidy schedule. This observation is further supported by Figure B.13, which presents the correlation between the two measures. Results from an OLS regression (with intercept) reveal a correlation coefficient of 0.80 for the net-of-tax rate and 0.77 for the participation tax rate.

Shocks distribution. My quasi-experimental research design and the validity of my exposure measure rely on the assumption that shocks are quasi-randomly assigned. Specifically, it depends on the variation in the log-growth of net-of-tax rates $\Delta^{sim} \ln(1 - \text{MTR}_{g,t})$ and participation tax rates $\Delta^{sim} \ln(1 - \text{ATR}_{g,t})$, as well as the distribution of the average exposure

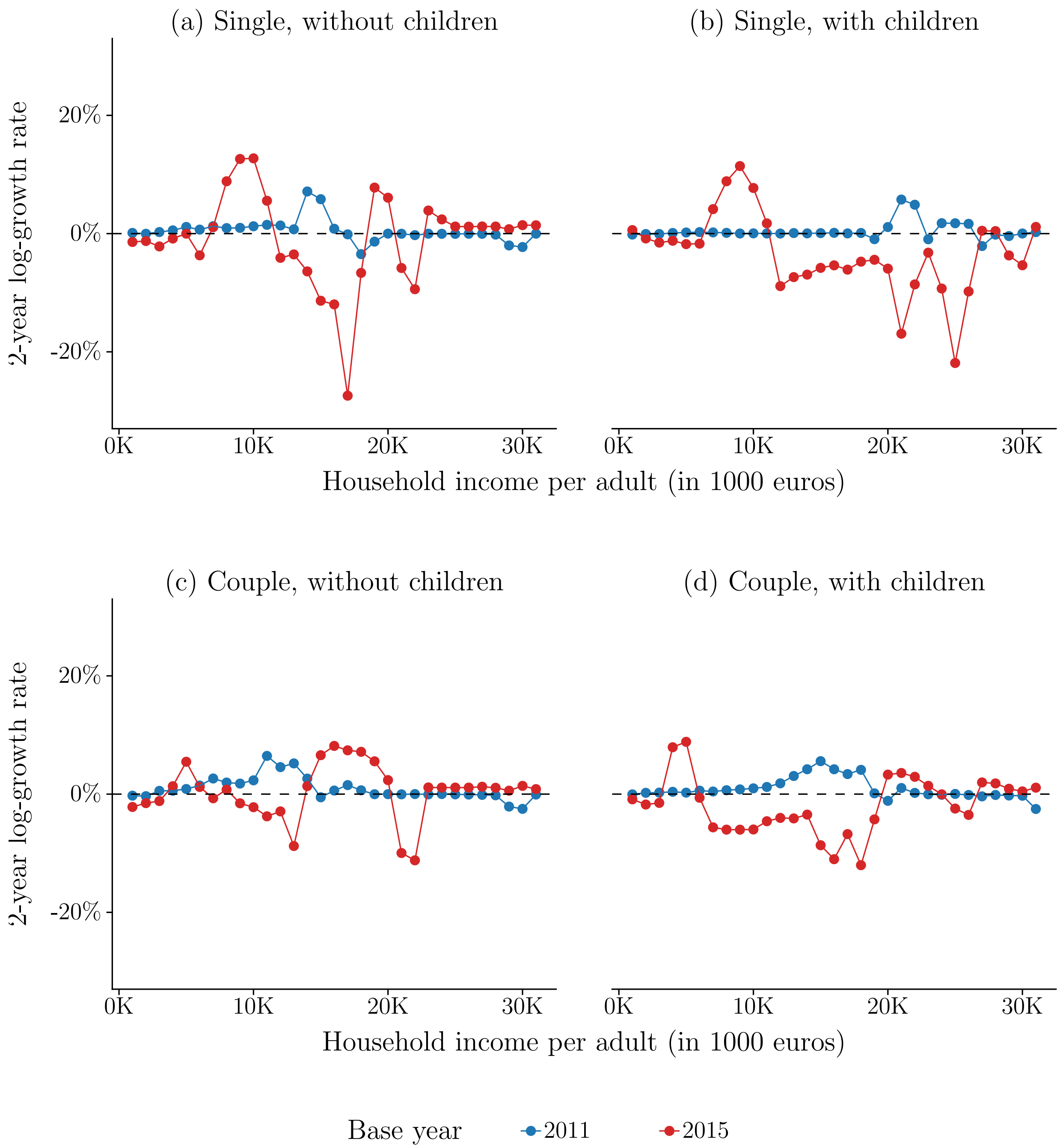
[13] I also provide the same plots using an alternative definition of the labor market level variables, employing cross-sectional weights, in Figure B.9 and Figure B.10. The results are similar, consistent with the fact that my sample is representative of the French population.

Figure 2: $\Delta^{sim} \ln(1 - \text{ATR}_{g,t})$ by treatment group, for base year 2011 and 2015



Notes: The figure plots the two-year change in the log of the participation tax rate at the treatment group-level, for base year 2011 and 2015 and considering the full tax and redistribution system. The tax 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 3: $\Delta^{sim}\ln(1-\mathrm{MTR}_{g,t})$ by treatment group, for base year 2011 and 2015



Notes: The figure plots the two-year change in the log of the net-of-tax rate at the treatment group-level, for base year 2011 and 2015 and considering the full tax and redistribution system. The tax 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).

$S_{g,t}$ across treatment groups. Following Borusyak, Hull, and Jaravel (2022), I assess the validity of the shift-share IV design by summarizing shocks at the treatment group levels. This highlights the source of variation used for identification while preserving the interpretation of local labor market level causal effects.

Table 2 presents the summary statistics for the net-of-tax rates and participation tax rates, along with additional information about the effective sample size. All statistics are weighted by the average exposure share $S_{g,t}$. I provide two sets of statistics for the shocks. Panel (a) reports statistics using raw values, while panel (b) reports statistics after residualization on year fixed-effects.[14]

Starting with the raw shocks in panel (a), the distribution of the log-growth of net-of-tax rates (respectively, participation tax rates) is left-skewed. It exhibits a mean of -0.023 (respectively, -0.012), a median of -0.007 (respectively, -0.010), with a standard deviation of 0.055 (respectively, 0.017). The 5th percentile is equal to -0.112 (respectively, -0.044), and the 95th percentile is equal to 0.055 (respectively, 0.014). This suggests a substantial degree of variation: there is a 17 percentage point difference between the log-growth rates of the 5th and 95th percentiles for the net-of-tax rate, and a 6 percentage point difference for the participation tax rate.

Next, I examine the distribution of shock residuals from a regression on year fixed-effects (panel (b)). The distribution of shocks is more symmetric, with mean and median close to 0. It also confirms that there is still substantial variation, with standard deviations similar to those in panel (a).

Finally, I report summary statistics for the sample in panel (c). The effective sample size, as measured by the inverse Herfindahl index, is 261. This confirms that the effective sample size is large. Consistent with this result, the largest share accounts for less than 1%. The number of unique treatment groups (combinations of household income bins, a couple

[14] I also provide summary statistics using an alternative definition of the labor market level variables, employing cross-sectional weights. This can be found in Table A.1. However, this is not my preferred measure because the weights are designed to match the aggregate distribution of incomes at the national level (not only labor earnings) and are not longitudinal weights. Nevertheless, the results are similar

Table 2: Shocks summary statistics

	Mean	Standard deviation	p5	Median	p95
		(a) Shocks			
$\Delta^{sim}\ln(1\text{-MTR}_{gt})$	-0.023	0.055	-0.112	-0.007	0.055
$\Delta^{sim}\ln(1\text{-ATR}_{gt})$	-0.012	0.017	-0.044	-0.010	0.014
		(b) Shocks with year F.E			
$\Delta^{sim}\ln(1\text{-MTR}_{gt})$	0	0.053	-0.077	0.003	0.068
$\Delta^{sim}\ln(1\text{-ATR}_{gt})$	0	0.015	-0.024	0	0.025
		(c) Sample size			
1/HHI	261	261	261	261	261
Largest share	0.008	0.008	0.008	0.008	0.008
Treatment groups	124	124	124	124	124
Treatment groups x periods	620	620	620	620	620

Notes: This table summarizes the distribution of instruments (net-of-tax rate and participation rate) across treatment groups. Shocks are two-year difference in log. All statistics are weighted by the average treatment group exposure share $s_{g,t}$ for 2011-2015. In the second panel, shocks are first residualized on year fixed-effects. I also report information about the sample: the inverse of the Herfindal index, the largest average exposure share, the number of units and the total number of observations.

dummy, and having children dummy) is 124 per year, with a total of 620 pooled observations over 5 years.

5 Results

This section presents the main estimates using the shift-share IV research design outlined in Section 3. Specifically, I report estimates from equation (6), weighted by the average exposure of treatment group $S_{g,t}$. My outcomes of interest are the 2-year log-growth rates in the total number of hours worked $\Delta\ln(\text{hours}) = \Delta\ln(L_{m,t})$, in the average hourly wage $\Delta\ln(\text{wage}) = \Delta\ln(w_{m,t})$, and the sum of labor earnings $\Delta\ln(\text{labor earnings}) = \Delta\ln(L_{m,t}) + \Delta\ln(w_{m,t})$ at the local labor market level. In my main analysis, I report standard errors clustered at the household income level. Base-year controls at the labor market level include the share of full-time workers, the share of individuals working a complete year, and the share of workers close to the minimum wage.[15]

5.1 Underlying Variation Behind the Shift-share IV

I start by providing graphical evidence for the variation underlying the shift-share IV.

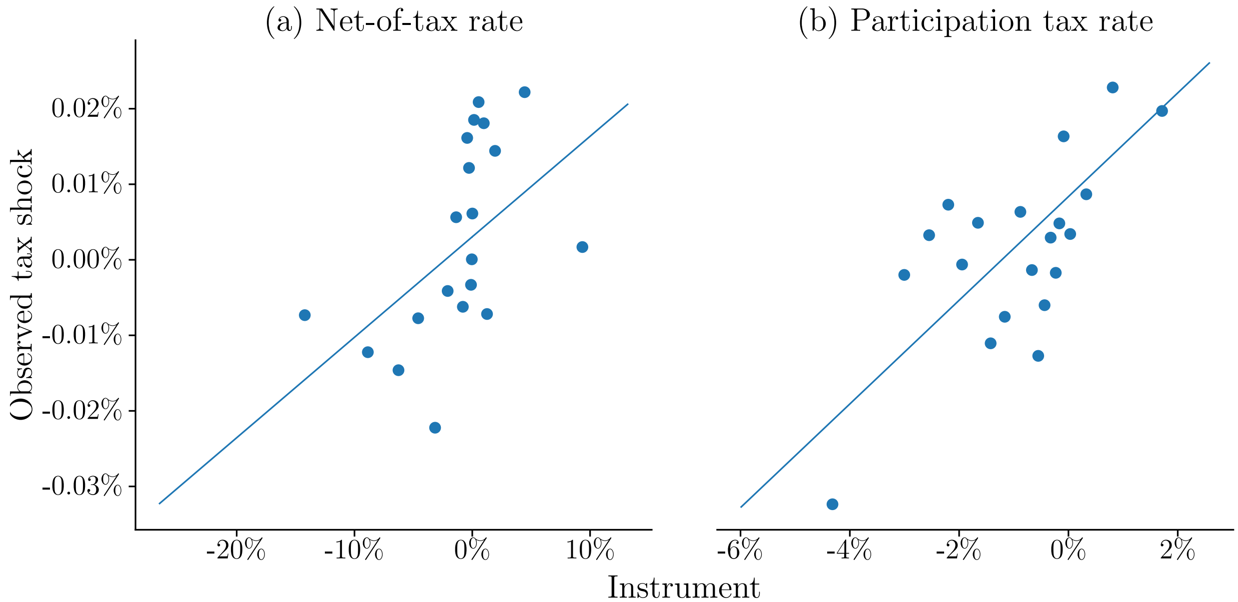
First-stage correlations. I begin by examining the relevance condition for both the net-of-tax rate instrument and the participation tax rate instrument, using a graphical representation of the first stage. Figure 4 illustrates the correlation between the instrument $\theta^{sim}_{g,t}$ and observed tax shock $\tilde{X}^{\theta}_{g,t}$. Panel (a) and Panel (b) display correlations for the net-of-tax rate and the participation tax rate, respectively. For each tax measure, I control for labor market-level fixed-effects, year fixed-effects, base-year socio-economic controls, and the other tax measure. Both observed tax shocks display a sharp positive relationship with their respective instrument, suggesting strong first-stages.

Correlations between outcomes and instruments. Starting with the employment side, Figure 5 illustrates the relationship between the instrument $\theta^{sim}_{g,t}$ and the employment response, expressed at the treatment group level consistent with Equation 6. Panel (a) (respectively, panel (b)) first presents the response concerning a change in the net-of-tax rate (respectively, participation tax rate). For each instrument, I control for labor market-level fixed-effects, year fixed-effects, base-year socio-economic controls, and the other tax instrument. Hours are not correlated with the net-of-tax rate, but they are strongly positively correlated with the participation tax rate.

Next, Figure 6 displays the same analysis but for the wage response. Panel (a) (respectively, panel (b)) presents the response concerning a change in the net-of-tax rate (respec-

[15] I define 'close to the minimum wage' as having a hourly wage rate below €9, expressed in taxable labor earnings. In 2011, the hourly minimum wage was slightly above €8 for a full-time worker.

Figure 4: First-stage estimations, SSIV research design



Notes: The figure plots the reduced-form relationship underlying the shift-share IV research design. It plots the correlation between the observed tax shocks and the corresponding instruments. Panel (a) shows the correlation for the net-of-tax rate, controlling for the participation tax rate. Panel (b) shows the correlation for participation tax rate, controlling for the net-of-tax rate. Observation are weighted by the average treatment group exposure share $S_{g,t}$. The x-axis shows the simulated instruments and the y-axis the average observed tax shocks. Each dot represents 5% of the data.

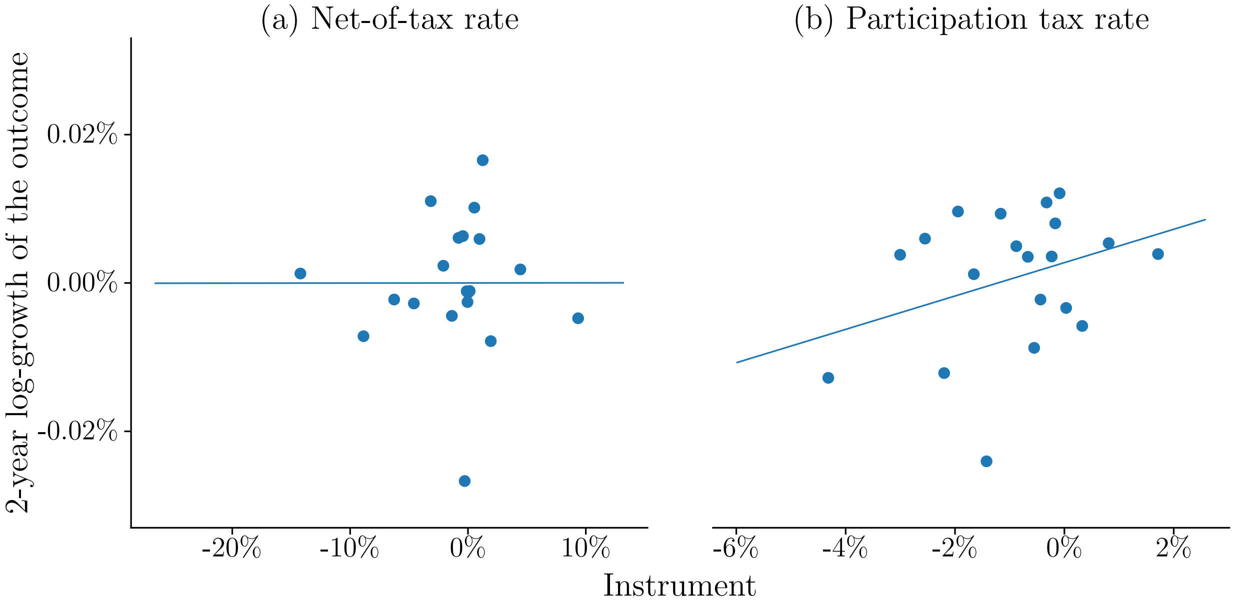
tively, participation tax rate). Similarly, the hourly wage is not correlated with the net-of-tax rate, but it is strongly negatively correlated with the participation tax rate.

Finally, Figure B.14 (respectively, Figure B.15) shows falsification tests for the employment response (respectively, the wage response). It correlates past outcomes with current shocks, providing an intuitive placebo test. For both the net-of-tax rate and the participation tax rate, there is no correlation between instruments and outcomes.

5.2 Shift-share IV Results

Baseline results. Table 3 presents the estimates for the wage and employment effects derived from the shift-share IV research design, based on my preferred specification. It uses simulated tax shocks as instruments for changes in net-of-tax rates and participation tax

Figure 5: Reduced-form employment relationships

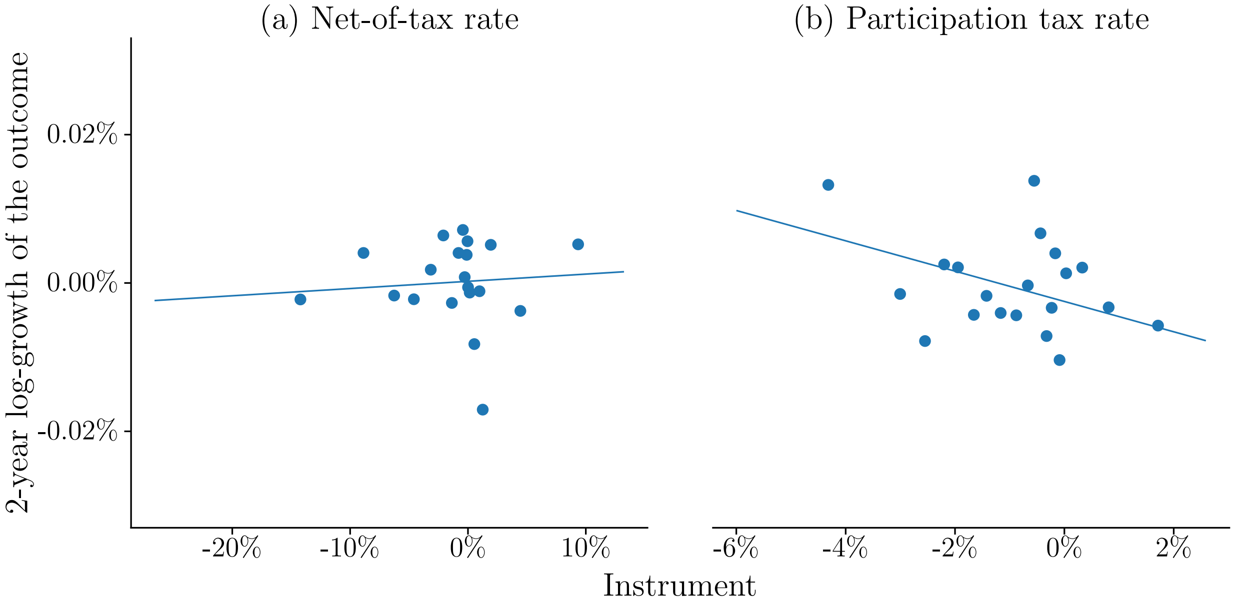


Notes: The figure plots the reduced-form relationship between two-year change in the log of hours at the labor market level and the two instruments. The two tax shocks are the two-year change in the log of the participation tax rate and net-of-tax rate. Panel (a) shows the correlations with respect to the net-of-tax rate and panel (b) shows the correlations with respect to the participation tax rate. Outcomes are first residualized on a set of labor market fixed-effects, year fixed-effects, a set of socio-economic characteristics in the initial year and the other tax shock. The corresponding regression is weighted by the average treatment group exposure share $S_{g,t}$. The x-axis shows the shock size (simulated instruments) and the y-axis the average change in outcome. Each dot represents 5% of the data.

rates. The first-stage F-statistics are high, approximately 40 for the net-of-tax rate and 198 for the participation tax rate, consistent with strong shift-share instruments.

Employment effects are reported in column (1). The point estimate for the elasticity with respect to the net-of-tax rate is 0.043, and it is 0.338 for the elasticity with respect to the participation tax rate. Only the second coefficient is statistically significant. In column (2), similar elasticities for the hourly wage rate are presented. The point estimate is 0.051 for the elasticity with respect to the net-of-tax rate and -0.278 for the elasticity with respect to the participation tax rate. Again, only the second coefficient is statistically significant. An increase of 10% in the participation tax rate is associated with a 3.38% increase in the number of hours worked and a 2.78% decrease in the average hourly wage, compared to the

Figure 6: Reduced-form wage relationships



Notes: The figure plots the reduced-form relationship between two-year change in the log hourly wage at the labor market level and the two instruments. The two tax shocks are the two-year change in the log of the participation tax rate and net-of-tax rate. Panel (a) shows the correlations with respect to the net-of-tax rate and panel (b) shows the correlations with respect to the participation tax rate. Outcomes are first residualized on a set of labor market fixed-effects, year fixed-effects, a set of socio-economic characteristics in the initial year and the other tax shock. The corresponding regression is weighted by the average treatment group exposure share $S_{g,t}$. The x-axis shows the shock size (simulated instruments) and the y-axis the average change in outcome. Each dot represents 5% of the data.

situation without any change in the wage subsidy schedule. Finally, column (3) reports the results for labor earnings, which is the sum of the wage and employment effects. The point estimates are 0.093 and 0.06, and both are non-significant. The wage effect is approximately equal to the employment effect, indicating that labor earnings are not positively affected by an increase in wage subsidies.

A note of caution regarding the interpretation of the results: the null effects on labor earnings should not be interpreted as stagnation in absolute value. The set of fixed-effects, including year, labor market level, and treatment groups, controls for specific labor supply and labor demand trends, as well as year-specific shocks. In France, labor earnings are growing positively on average. An increase in the net-of-tax rate or participation tax rate

Table 3: Shift-share IV estimates

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	0.043	0.051	0.093
	(0.097)	(0.075)	(0.154)
Δ ln(1-ATR)	0.338***	-0.278***	0.060
	(0.050)	(0.056)	(0.065)
Observations	620	620	620
F-test (1st stage), Δ ln(1-MTR)	39.4	39.4	39.4
F-test (1st stage), Δ ln(1-ATR)	197.6	197.6	197.6
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

leads to a decrease in the prospective wage. In other words, in the absence of wage subsidies, labor market outcomes would have experienced higher growth rates.

Economic incidence of wage subsidies. The wage effect suggests an average pass-through of 28% of wage subsidies to wages. This result is qualitatively consistent with the limited literature on the economic incidence of wage subsidies. Leigh (2010) found that an increase of 10% in the EITC decreases the hourly wage rate by 5% for high school dropouts using variation in US state-level EITC. His analysis uses wage and employment levels, while mine focuses on log-growth rates. Consequently, my estimates are compatible with reasonable incidence parameters for wage subsidies. Furthermore, 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 individuals who are low-wage earners. Still, my results are similar to his for a reasonable set of micro elasticities. Additionally, zurla2022firm identifies a pass-through rate of 50% within the context of a substantial Italian EITC program. The pass-through in their study is higher than in mine for two reasons. First, zurla2022firm leverage variations in program exposure among different firms, while mine focuses on responses at the level of local labor markets. Second, the distribution of the Italian wage subsidy is administered by the firm, while it is directly distributed to workers in the French context and is therefore less salient to the firm.

5.3 Robustness Checks

Falsification tests. To assess the validity of my research design, in particular assumption 2, I implement falsification tests from Borusyak, Hull, and Jaravel (2022) by regressing past outcomes on currents shocks. Intuitively, pre-reform outcomes should not exhibit any correlation with shocks occurring during the reform period. I employ the same shift-share IV research design as in the baseline results. In Table 4, I present presents the results from this analysis. I conduct this test for the two years following the reform, which reduces the sample size to 248 observations. Across all specifications, I find no evidence to reject the hypothesis that there is no relationship between current tax shocks and past outcomes. Furthermore, the standard errors are relatively high, indicating that this regression largely captures random noise. In sum, these findings validate the credibility of the shift-share IV design as a robust identification strategy.

Table 4: Falsification tests for the shift-share IV

	$\Delta\,\ln$(hours) (1)	$\Delta\,\ln$(wage) (2)	$\Delta\,\ln$(labor earnings) (3)
$\Delta\,\ln$(1-MTR)	-0.454	0.205	-0.249
	(0.602)	(0.555)	(1.01)
$\Delta\,\ln$(1-ATR)	-0.669	0.629	-0.040
	(0.964)	(0.644)	(1.48)
Observations	248	248	248
F-test (1st stage), $\Delta\,\ln$(1-MTR)	4.38	4.38	4.38
F-test (1st stage), $\Delta\,\ln$(1-ATR)	112.2	112.2	112.2
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV falsification tests. I regress the two-year change in the log of past labor market outcomes on current tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Alternative specifications. To further assess the robustness of my results, I implement two additional checks. First, I explore alternative model specifications compared to my baseline estimation. Specifically, I relax the requirements for fixed-effects, estimate heteroskedasticity-robust standard errors and use alternative regression weights. Second, I perform the same analysis separately for the net-of-tax and participation tax rates.

To start with, I explore if less stringent sets of fixed-effects and heteroskedasticity-robust instead of clustered standard errors have an impact on my results. Specifically, I divide the treatment group fixed-effects into three distinct sets: household income bin fixed-effects, a binary variable for couple status, and a binary variable for parental status. The results for these alternative specifications are presented in Table A.2. For the wage, employment, and labor earnings responses, the coefficients remain nearly identical to those in the baseline specification.

Then, I provide additional results using alternative regression weights while keeping the baseline specification unchanged. Instead of using the initial share of a local labor market in the national population, I employ the initial share of a local labor market in the national labor supply (measured by the number of hours worked). The results for the main specification are reported in Table A.5, and the results for the falsification tests are reported in Table A.6. Once again, the coefficients for wage, employment, and labor earnings responses are close to those in the baseline specification.[16]

Finally, I use the same shift-share IV approach as in the baseline analysis to regress the set of outcomes separately on each tax measure. If each tax measure captures a different response margin and if shocks are not completely correlated, the coefficients should not significantly differ from those in the baseline analysis. Table A.3 reports the shift-share IV estimates, and Table A.4 presents the corresponding falsification tests. In both cases, coefficients from separate regressions on each tax measure are close to those obtained from regressions including both tax measures.

6 Mechanisms and Discussion

Micro elasticities, extensive and intensive margin responses. My findings that the wage effect offsets the employment effect is interesting when considering micro elasticities.

[16]Results using an alternative definition of the labor market level variables with cross-sectional weights can be found in Table A.7, Table A.8, Table A.9, and Table A.10. However, this alternative measure is not my preferred choice as the weights are designed to match the aggregate income distribution at the national level, encompassing more than just labor earnings. Nevertheless, the qualitative findings are consistent with the main results.

It has two implications. First, there exist substantial labor supply responses, whether at the intensive or extensive margin. Second, labor demand is not completely elastic. Keeping the simple conceptual framework from subsection 3.1 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. This outcome is consistent with the presence of significant wage and employment effects at the labor market level.

Using my preferred specification (as presented in Table 3) and assuming a compensated elasticity of labor supply $\varepsilon^c = 0$ (indicating no response to changes in the net-of-tax rate), it suggests an elasticity of labor demand $\varepsilon^d \approx$ -1.2 and a labor supply participation elasticity $\varepsilon^p \approx 0.5$. This participation elasticity magnitude is consistent with findings from Eissa and Liebman (1996) and Whitmore Schanzenbach and Strain (2021).[17]

The micro-elasticities and the pass-through effect of wage subsidies on wages align with simulations from Rothstein (2010). He finds that under the assumption of a labor demand elasticity $\varepsilon^d \approx$ -1, a labor supply participation elasticity $\varepsilon^p \approx 0.5$ and a compensated elasticity of labor supply $\varepsilon^c = 0$, that a one-percentage-point increase in the participation tax rate leads to a 33% increase in labor supply and a 33% decrease in the wage rate.

Minimum wage. Wage subsidies are designed to target low-wage earners, a population more likely to be close to the minimum wage. In France, the minimum wage may have a greater influence compared to other countries like the United States, potentially impacting both wage and employment effects. To address this concern, my estimation strategy includes a dummy variable for the proximity to the hourly minimum wage in the initial period.

I also provide additional evidence against the argument that the results can be solely

[17] Another plausible explanation for the observed response magnitude concerning the participation tax rate is the concept of "ironing," where individuals linearize their tax schedule based on their average tax rate. Rees-Jones and Taubinsky (2020) found that 43% of the US population engages in ironing. In this context, wage and employment responses to changes in the participation tax rate result from a combination of labor supply elasticity at the intensive and extensive margins, along with the elasticity of labor demand.

driven by changes in the hourly minimum wage. First, in Figure B.16, the cross-sectional distribution of the share of workers, categorized by their distance to the minimum wage, remains stable over time. Individuals earning below 1.1 times the minimum wage constitute nearly 10% of the working population.

Second, Figure B.17 illustrates the transitions between different distance-to-minimum-wage categories between two consecutive periods. It shows that individuals starting below 1.1 times the minimum wage have a 50% chance of moving to a different category, indicating significant wage growth beyond the minimum wage over time.

Finally, Figure B.18 confirms this finding by showing the number of consecutive years spent in proximity to the minimum wage, assuming one starts a period at the minimum wage. It indicates that 70% of individuals spend only a year or less at the minimum wage. It is consistent with findings from Zurla (2022), suggesting responsiveness in earnings growth rather than levels, due to the presence of downward wage rigidities. Therefore, the pass-through coefficient of 28% that I find represents a conservative estimate and serves as a lower bound for the pass-through that would have occurred in the absence of any minimum wage.

More broadly, Vergara (2022) highlights that a binding minimum wage, when designed in conjunction with taxes and benefits, can serve as a important tool for redistribution. It can effectively reduce the pass-through of wage subsidies to wages for low-skilled workers, increasing overall efficiency.

Limitations. My research design has three limitations. First, due to data constraints, I am limited to only two post-reform years. While this time frame is reasonable for identifying short-term wage and employment responses to changes in wage subsidies, outcomes can possibly differ in the long run. In the short term, labor demand is relatively inelastic, whereas in the long term, employers could potentially make more substantial adjustments to their production. Consequently, my results offer an lower-bound estimates of the wage and employment effects in the long run.

Secondly, individuals may gradually adapt to the reform. Labor supply responses might experience delays if individuals do not immediately respond to alterations in wage subsidies. This is especially likely in contexts marked by salience effects, information gaps regarding wage subsidy programs, or infrequent wage renegotiations. Although my research design mitigates these concerns by examining two-year differences in log wages, hours worked, and labor earnings, it is still plausible that the employment effect could be higher in the long run.

Finally, my data reports taxable labor earnings, which do not encompass labor costs borne by the employer. Specifically, it excludes employer payroll taxes. During the period from 2013 to 2016, several reductions in employer payroll taxes were implemented, primarily targeting workers earning less than 3.5 times the national minimum wage.[18] While it is not possible to completely rule out the influence of these tax cuts on wages, I provide several reasons indicating that my results are not driven by them. 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 on workers, due to the absence of tax-benefit linkage. To be more specific, labor earnings, which are close to my definition, remain unaffected. Secondly, the non-linear nature of the tax and benefits schedule at the individual level ensures that my source of variation differs from that of the payroll tax reductions, especially when including a set of period, local labor market, and treatment group fixed effects.

7 Conclusion

This paper provides novel causal estimates regarding the wage and employment effects of wage subsidies at the local labor market level. 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

[18]For more details, see https://www.gouvernement.fr/action/la-reduction-des-charges-et-de-la-fiscalite-des-entreprises-et-la-relance-de-l-investissement.

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 -0.28 (respectively 0.34) with respect to the 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 28% on average.

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, 2022).

References

Aghion, Philippe et al. (2023). “Anatomy of Inequality and Income Dynamics in France”. In:

Agostinelli, Francesco, Emilio Borghesan, and Giuseppe Sorrenti (2021). *Welfare, Workfare and Labor Supply: A Unified Evaluation*. CHILD, Centre for Household, Income, Labour and Demographic Economics . . .

Auten, Gerald and Robert Carroll (1999). “The effect of income taxes on household income”. In: *Review of economics and statistics* 81.4, pp. 681–693.

Azmat, Ghazala (2019). “Incidence, salience, and spillovers: The direct and indirect effects of tax credits on wages”. In: *Quantitative Economics* 10.1, pp. 239–273.

Bastian, Jacob (2020). “The rise of working mothers and the 1975 earned income tax credit”. In: *American Economic Journal: Economic Policy* 12.3, pp. 44–75.

Bollinger, Christopher, Luis Gonzalez, and James P Ziliak (2009). “Welfare reform and the level and composition of income”. In: *Welfare reform and its long-term consequences for America’s poor*, pp. 59–103.

Borusyak, Kirill and Peter Hull (2023). “Negative weights are no concern in design-based specifications”. In: *Working paper*.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022). “Quasi-experimental shift-share research designs”. In: *The Review of Economic Studies* 89.1, pp. 181–213.

Bourguignon, François (2011). “Rapport final du comité national d’évaluation du RSA”. In: *La documentation française*.

Bozio, Antoine et al. (2024). “Does Tax-Benefit Linkage Matter for the Incidence of Payroll Taxes?” In:

Brewer, Mike and Hilary Hoynes (2019). “In-Work Credits in the UK and the US”. In: *Fiscal Studies* 40.4, pp. 519–560.

Chetty, Raj, John N Friedman, and Emmanuel Saez (2013). "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings". In: *American Economic Review* 103.7, pp. 2683–2721.

Chetty, Raj and Emmanuel Saez (2013). "Teaching the tax code: Earnings responses to an experiment with EITC recipients". In: *American Economic Journal: Applied Economics* 5.1, pp. 1–31.

De Chaisemartin, Clément and Xavier d'Haultfoeuille (2023). "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey". In: *The Econometrics Journal* 26.3, pp. C1–C30.

DREES (juillet 2021). *Minima sociaux et prestations sociales - Ménages aux revenus modestes et redistribution - Édition 2021*. Panoramas de la DREES.

DREES and CNAF (2017). *Rapport d'évaluation de la prime d'activité*. Tech. rep. Direction Générale De La Cohésion Sociale.

Eissa, Nada and Hilary Hoynes (2006). "Behavioral responses to taxes: Lessons from the EITC and labor supply". In: *Tax policy and the economy* 20, pp. 73–110.

Eissa, Nada and Jeffrey B Liebman (1996). "Labor supply response to the earned income tax credit". In: *The quarterly journal of economics* 111.2, pp. 605–637.

Ferriere, Axelle et al. (2023). "On the Optimal Design of Transfers and Income Tax Progressivity". In: *Journal of Political Economy Macroeconomics* 1.2, pp. 000–000.

Froemel, Maren and Charles Gottlieb (2021). "The Earned Income Tax Credit: Targeting the poor but crowding out wealth". In: *Canadian Journal of Economics/Revue canadienne d'économique* 54.1, pp. 193–227.

Gelber, Alexander M and Joshua W Mitchell (2012). "Taxes and time allocation: Evidence from single women and men". In: *The Review of Economic Studies* 79.3, pp. 863–897.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik instruments: What, when, why, and how". In: *American Economic Review* 110.8, pp. 2586–2624.

Grogger, Jeffrey (2003). “The effects of time limits, the EITC, and other policy changes on welfare use, work, and income among female-headed families”. In: *Review of Economics and statistics* 85.2, pp. 394–408.

Gruber, Jon and Emmanuel Saez (2002). “The elasticity of taxable income: evidence and implications”. In: *Journal of public Economics* 84.1, pp. 1–32.

Hamermesh, Daniel S (1996). *Labor demand*. princeton University press.

Hotz, V. Joseph (2003). “The Earned Income Tax Credit”. In: *Means-Tested Transfer Programs in the United States*. National Bureau of Economic Research, Inc, pp. 141–198. URL: https://EconPapers.repec.org/RePEc:nbr:nberch:10256.

Hotz, V. Joseph and John Karl Scholz (2006). *Examining the effect of the earned income tax credit on the labor market participation of families on welfare*.

Hoynes, Hilary (2019). “The earned income tax credit”. In: *The Annals of the American Academy of Political and Social Science* 686.1, pp. 180–203.

Hoynes, Hilary and Jesse Rothstein (2016). *Tax policy toward low-income families*. Tech. rep. National Bureau of Economic Research.

Imbens, Guido W. (2014). “Instrumental Variables: An Econometrician’s Perspective”. In: *Statistical Science* 29.3, pp. 323–358. ISSN: 08834237, 21688745. URL: http://www.jstor.org/stable/43288511 (visited on 01/18/2024).

Kleven, Henrik (2019). *The EITC and the extensive margin: A reappraisal*. Tech. rep. National Bureau of Economic Research.

Kopczuk, Wojciech (2005). “Tax bases, tax rates and the elasticity of reported income”. In: *Journal of Public Economics* 89.11-12, pp. 2093–2119.

Leigh, Andrew (2010). “Who benefits from the earned income tax credit? Incidence among recipients, coworkers and firms”. In: *The BE Journal of Economic Analysis & Policy* 10.1.

Meyer, Bruce D (2010). “The effects of the Earned Income Tax Credit and recent reforms”. In: *Tax policy and the economy* 24.1, pp. 153–180.

Meyer, Bruce D and Dan T Rosenbaum (2001). "Welfare, the earned income tax credit, and the labor supply of single mothers". In: *The quarterly journal of economics* 116.3, pp. 1063–1114.

Moffitt, Robert and Mark Wilhelm (2000). *Labor supply decisions of the affluent.*

Nichols, Austin and Jesse Rothstein (2015). "The earned income tax credit". In: *Economics of Means-Tested Transfer Programs in the United States, Volume 1.* University of Chicago Press, pp. 137–218.

Ortigueira, Salvador and Nawid Siassi (2022). "The us tax-transfer system and low-income households: Savings, labor supply, and household formation". In: *Review of Economic Dynamics* 44, pp. 184–210.

Rees-Jones, Alex and Dmitry Taubinsky (2020). "Measuring "schmeduling"". In: *The Review of Economic Studies* 87.5, pp. 2399–2438.

Rothstein, Jesse (2010). "Is the EITC as good as an NIT? Conditional cash transfers and tax incidence". In: *American economic Journal: economic policy* 2.1, pp. 177–208.

Vergara, Damián (2022). "Minimum Wages and Optimal Redistribution". In: *arXiv preprint arXiv:2202.00839.*

Whitmore Schanzenbach, Diane and Michael R Strain (2021). "Employment effects of the Earned Income Tax Credit: Taking the long view". In: *Tax Policy and the Economy* 35.1, pp. 87–129.

Zurla, Valeria (2022). "Firm Responses to Earned Income Tax Credits: Evidence from Italy". In:

A Tables

Table A.1: Shock and labor market summary statistics, with cross-sectional weights

	Mean	Standard deviation	p5	Median	p95
		(a) Shocks			
$\Delta^{sim}\ln(1\text{-MTR}_{gt})$	-0.023	0.055	-0.113	-0.007	0.056
$\Delta^{sim}\ln(1\text{-ATR}_{gt})$	-0.012	0.017	-0.045	-0.010	0.014
		(b) Shocks with year F.E			
$\Delta^{sim}\ln(1\text{-MTR}_{gt})$	0	0.053	-0.077	0.003	0.068
$\Delta^{sim}\ln(1\text{-ATR}_{gt})$	0	0.015	-0.024	0	0.025
		(c) Sample size			
1/HHI	262	262	262	262	262
Largest share	0.008	0.008	0.008	0.008	0.008
Treatment groups	124	124	124	124	124
Treatment groups x periods	620	620	620	620	620
Cross-sectional weights	Yes	Yes	Yes	Yes	Yes

Notes: This table summarizes the distribution of instruments (net-of-tax rate and participation rate) across treatment groups. Shocks are two-year difference in log. All statistics are weighted by the average treatment group exposure share $s_{g,t}$ for 2011-2015. Variables are constructed using cross-sectional administrative weights. In the second panel, shocks are first residualized on year fixed-effects. I also report information about the sample: the inverse of the Herfindal index, the largest average exposure share, the number of units and the total number of observations.

Table A.2: Shift-share IV estimates, alternative specifications

	Δ ln(hours)				Δ ln(wage)				Δ ln(labor earnings)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ ln(1-MTR)	0.054	0.055	0.053	0.043	0.051	0.048	0.049	0.051	0.106	0.102	0.102	0.093
	(0.117)	(0.115)	(0.113)	(0.178)	(0.071)	(0.073)	(0.071)	(0.130)	(0.162)	(0.162)	(0.161)	(0.147)
Δ ln(1-ATR)	0.342***	0.341***	0.341***	0.338***	-0.288***	-0.281***	-0.281***	-0.278**	0.054	0.060	0.060	0.060
	(0.052)	(0.055)	(0.055)	(0.126)	(0.057)	(0.057)	(0.057)	(0.118)	(0.065)	(0.067)	(0.067)	(0.117)
Observations	620	620	620	620	620	620	620	620	620	620	620	620
F-test (1st stage), Δ ln(1-MTR)	31.4	32.3	32.3	31.5	31.4	32.3	32.3	31.5	31.4	32.3	32.3	31.5
F-test (1st stage), Δ ln(1-ATR)	157.0	171.3	171.2	157.9	157.0	171.3	171.2	157.9	157.0	171.3	171.2	157.9
Standard errors	Clust.	Clust.	Clust.	Hetero.	Clust.	Clust.	Clust.	Hetero.	Clust.	Clust.	Clust.	Hetero.
Treatment group F.E				✓				✓				✓
Children FE			✓				✓				✓	
Couple F.E		✓	✓			✓	✓			✓	✓	
HH income F.E	✓	✓	✓		✓	✓	✓		✓	✓	✓	
Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor market F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1), (2), (3) and (4)), the hourly wage rate (panel (5), (6), (7) and (8)) and the sum of labor earnings (panel (9), (10), (11) and (12)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level, except for panels (4), (8) and (12) that estimate heteroskedasticity-robust standard errors. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.3: Shift-share IV estimates by tax measure

	Δ ln(hours)			Δ ln(wage)			Δ ln(labor earnings)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln(1-MTR)	0.037		0.043	0.055		0.051	0.092		0.093
	(0.100)		(0.097)	(0.162)		(0.075)	(0.139)		(0.154)
Δ ln(1-ATR)		0.329***	0.338***		-0.288***	-0.278***		0.041	0.060
		(0.040)	(0.050)		(0.067)	(0.056)		(0.078)	(0.065)
Observations	620	620	620	620	620	620	620	620	620
F-test (1st stage), Δ ln(1-MTR)	68.0		39.4	68.0		39.4	68.0		39.4
F-test (1st stage), Δ ln(1-ATR)		395.7	197.6		395.7	197.6		395.7	197.6
Treatment group F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor market F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panels (1), (2) and (3)), the hourly wage rate (panels (4), (5) and (6)) and the sum of labor earnings (panels (7), (8) and (9)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.4: Falsification tests for the shift-share IV by tax measure

	Δ ln(hours)			Δ ln(wage)			Δ ln(labor earnings)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ ln(1-MTR)	-0.576		-0.454	0.320		0.205	-0.256		-0.249
	(0.438)		(0.602)	(0.561)		(0.555)	(0.810)		(1.01)
Δ ln(1-ATR)		-0.848	-0.669		0.710*	0.629		-0.138	-0.040
		(1.03)	(0.964)		(0.370)	(0.644)		(1.32)	(1.48)
Observations	248	248	248	248	248	248	248	248	248
F-test (1st stage), Δ ln(1-MTR)	7.48		4.38	7.48		4.38	7.48		4.38
F-test (1st stage), Δ ln(1-ATR)		222.0	112.2		222.0	112.2		222.0	112.2
Treatment group F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor market F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Base-year controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports coefficients from shift-share IV falsification tests. I regress the two-year change in the log of past labor market outcomes on current tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.5: Shift-share estimates, with hours-weighted labor markets

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	0.033	0.043	0.076
	(0.104)	(0.079)	(0.162)
Δ ln(1-ATR)	0.363***	-0.290***	0.072
	(0.049)	(0.057)	(0.066)
Observations	620	620	620
F-test (1st stage), Δ ln(1-MTR)	38.4	38.4	38.4
F-test (1st stage), Δ ln(1-ATR)	195.8	195.8	195.8
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the total number of hours worked at the national level in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.6: Falsification tests for the shift-share IV, with hours-weighted labor markets

	$\Delta\ln$(hours) (1)	$\Delta\ln$(wage) (2)	$\Delta\ln$(labor earnings) (3)
$\Delta\ln$(1-MTR)	-0.352	0.145	-0.207
	(0.569)	(0.558)	(0.986)
$\Delta\ln$(1-ATR)	-0.824	0.673	-0.151
	(0.942)	(0.646)	(1.46)
Observations	248	248	248
F-test (1st stage), $\Delta\ln$(1-MTR)	3.87	3.87	3.87
F-test (1st stage), $\Delta\ln$(1-ATR)	104.2	104.2	104.2
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV falsification tests. I regress the two-year change in the log of past labor market outcomes on current tax shocks, weighted by the share of the labor market in the total number of hours worked at the national level in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panels (1), (2) and (3)), the hourly wage rate (panels (4), (5) and (6)) and the sum of labor earnings (panels (7), (8) and (9)). Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.7: Shift-share estimates, with cross-sectional weights

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	-0.165	0.030	-0.135
	(0.156)	(0.073)	(0.212)
Δ ln(1-ATR)	0.541***	-0.224***	0.317**
	(0.079)	(0.059)	(0.118)
Observations	620	620	620
F-test (1st stage), Δ ln(1-MTR)	40.2	40.2	40.2
F-test (1st stage), Δ ln(1-ATR)	194.6	194.6	194.6
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Variables are constructed using cross-sectional administrative weights. Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.8: Falsification tests for the shift-share IV, with cross-sectional weights

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	-1.68	0.088	-1.59
	(1.34)	(0.537)	(1.77)
Δ ln(1-ATR)	0.077	0.778	0.855
	(1.99)	(0.630)	(2.55)
Observations	248	248	248
F-test (1st stage), Δ ln(1-MTR)	4.54	4.54	4.54
F-test (1st stage), Δ ln(1-ATR)	111.4	111.4	111.4
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV falsification tests. I regress the two-year change in the log of past labor market outcomes on current tax shocks, weighted by the share of the labor market in the national population in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Variables are constructed using cross-sectional administrative weights. Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.9: Shift-share estimates, with hours-weighted labor markets and cross-sectional weights

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	-0.199	0.020	-0.179
	(0.159)	(0.076)	(0.219)
Δ ln(1-ATR)	0.527***	-0.241***	0.287**
	(0.082)	(0.060)	(0.121)
Observations	620	620	620
F-test (1st stage), Δ ln(1-MTR)	39.3	39.3	39.3
F-test (1st stage), Δ ln(1-ATR)	192.1	192.1	192.1
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV regressions of the two-year change in the log of labor market outcomes on tax shocks, weighted by the share of the labor market in the total number of hours worked at the national level in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Variables are constructed using cross-sectional administrative weights. Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

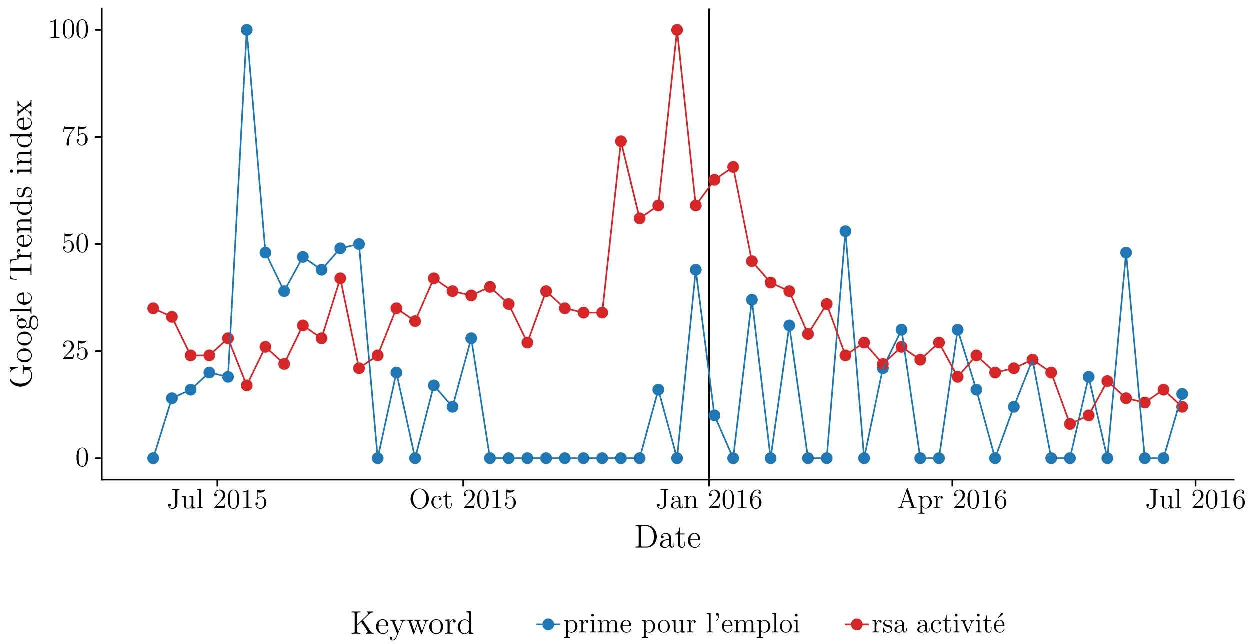
Table A.10: Falsification tests for the shift-share IV, with hours-weighted labor markets and cross-sectional weights

	Δ ln(hours) (1)	Δ ln(wage) (2)	Δ ln(labor earnings) (3)
Δ ln(1-MTR)	-1.55	0.013	-1.54
	(1.29)	(0.543)	(1.73)
Δ ln(1-ATR)	-0.179	0.823	0.645
	(1.90)	(0.629)	(2.46)
Observations	248	248	248
F-test (1st stage), Δ ln(1-MTR)	3.95	3.95	3.95
F-test (1st stage), Δ ln(1-ATR)	104.7	104.7	104.7
Treatment group F.E	✓	✓	✓
Period F.E	✓	✓	✓
Labor market F.E	✓	✓	✓
Base-year controls	✓	✓	✓

Notes: This table reports coefficients from shift-share IV falsification tests. I regress the two-year change in the log of past labor market outcomes on current tax shocks, weighted by the share of the labor market in the total number of hours worked at the national level in the initial period. The two tax shocks are the two-year change in the log of the net-of-tax rate and participation rate, instrumented by the corresponding simulated instruments. Labor market outcomes are the number of hours worked (panel (1)), the hourly wage rate (panel (2)) and the sum of labor earnings (panel (3)). Variables are constructed using cross-sectional administrative weights. Base-year controls include a set of socio-economic characteristics in the initial year. Results come from equivalent treatment group level regressions in order to obtain exposure-robust standard errors and F-statistics, and to include treatment group fixed-effects. Standard errors are clustered at the household income level. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

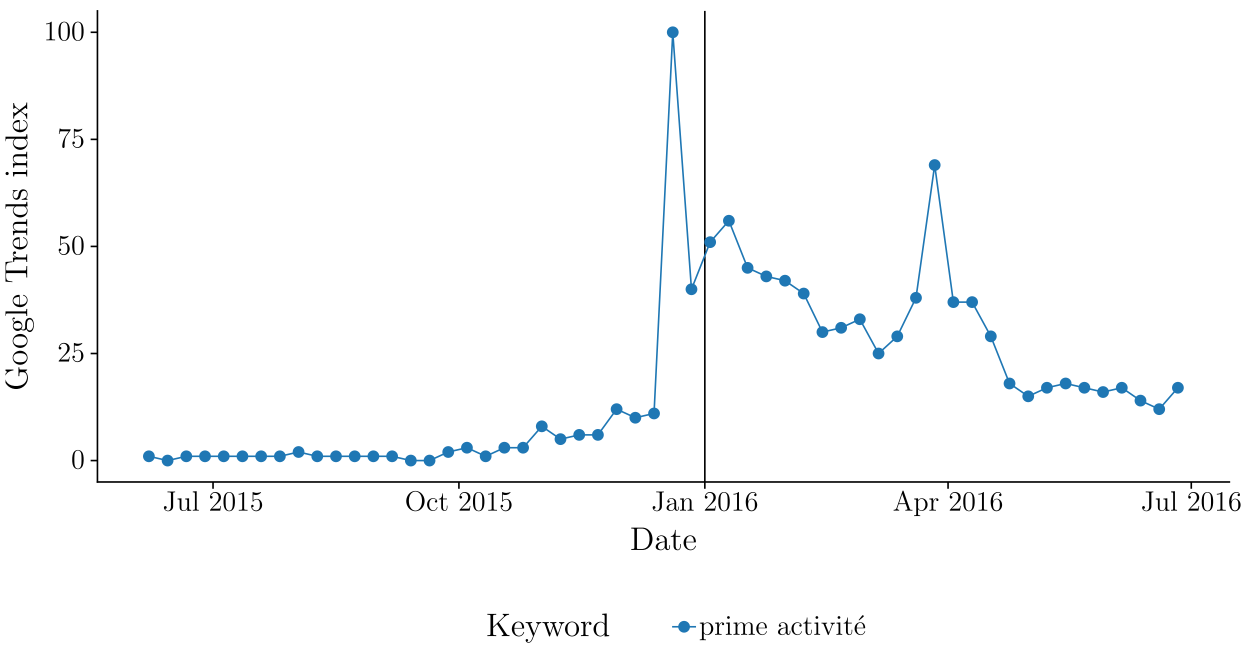
B Figures

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



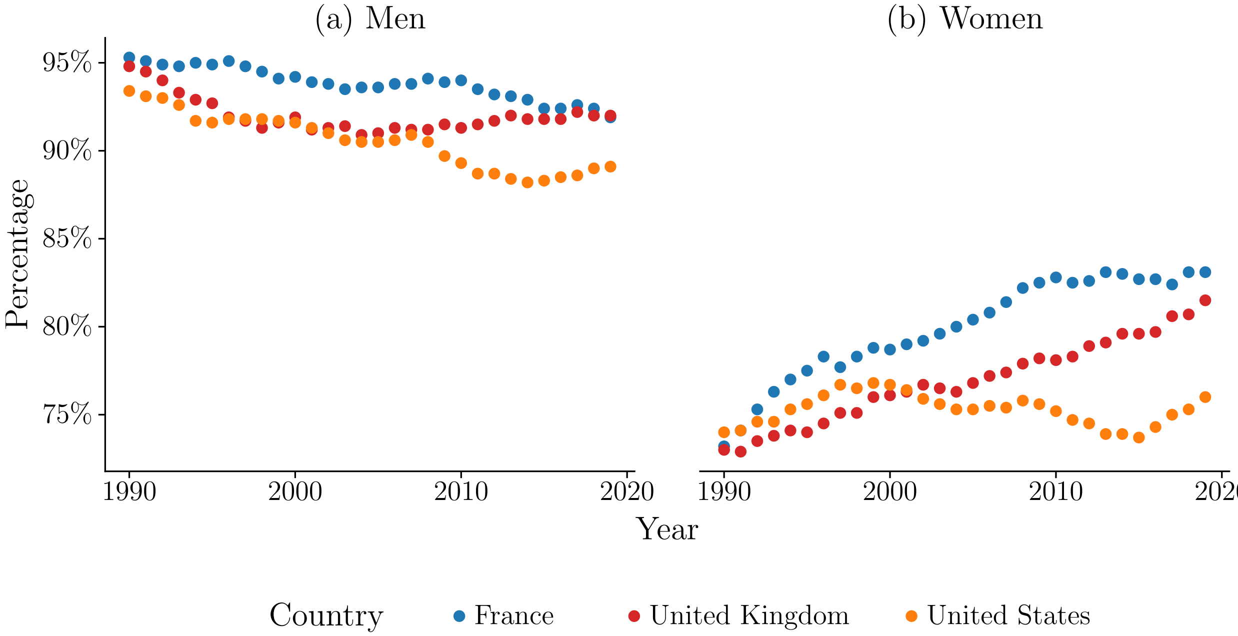
Notes: The figure plots times series for the Google Trends index for the two before-reform wage subsidy programs. More precisely, the two keywords are “prime pour l'emploi” and “rsa activité”. Each index is the result of a normalization between 0 and 100 of the number of search for these terms. 100 indicates 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



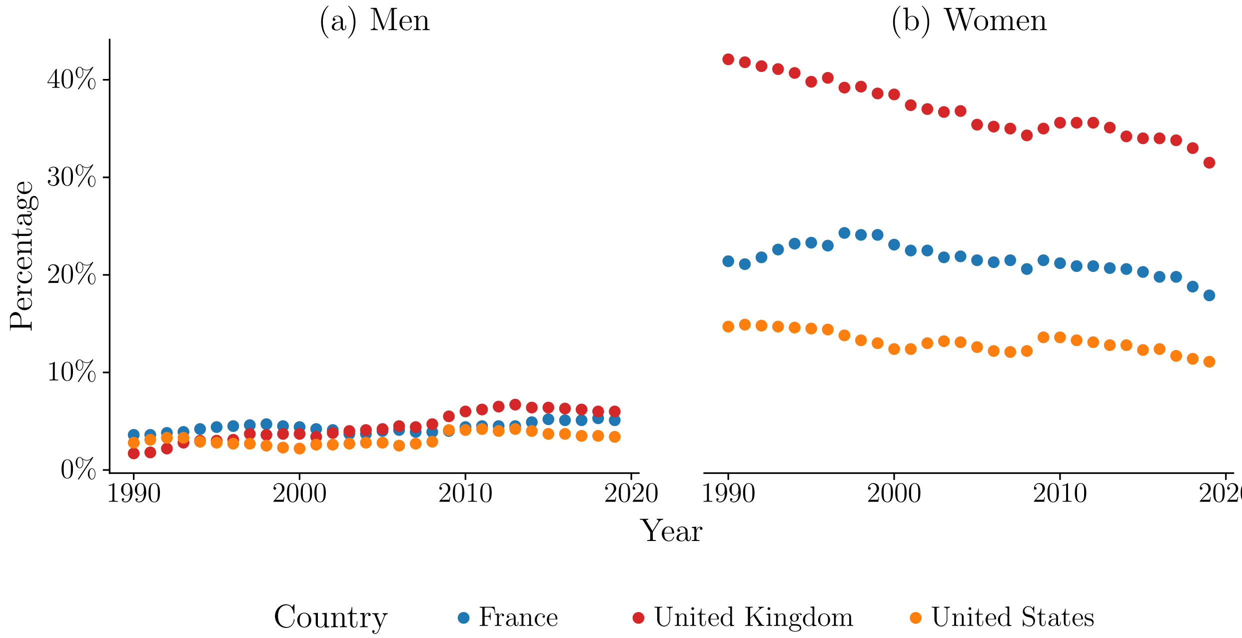
Notes: The figure plots times series for the Google Trends index for the two before-reform wage subsidy programs. More precisely, the keyword is "prime activité". Each index is the result of a normalization between 0 and 100 of the number of search for these terms. 100 indicates the day where the number 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: Labor force participation, by sex



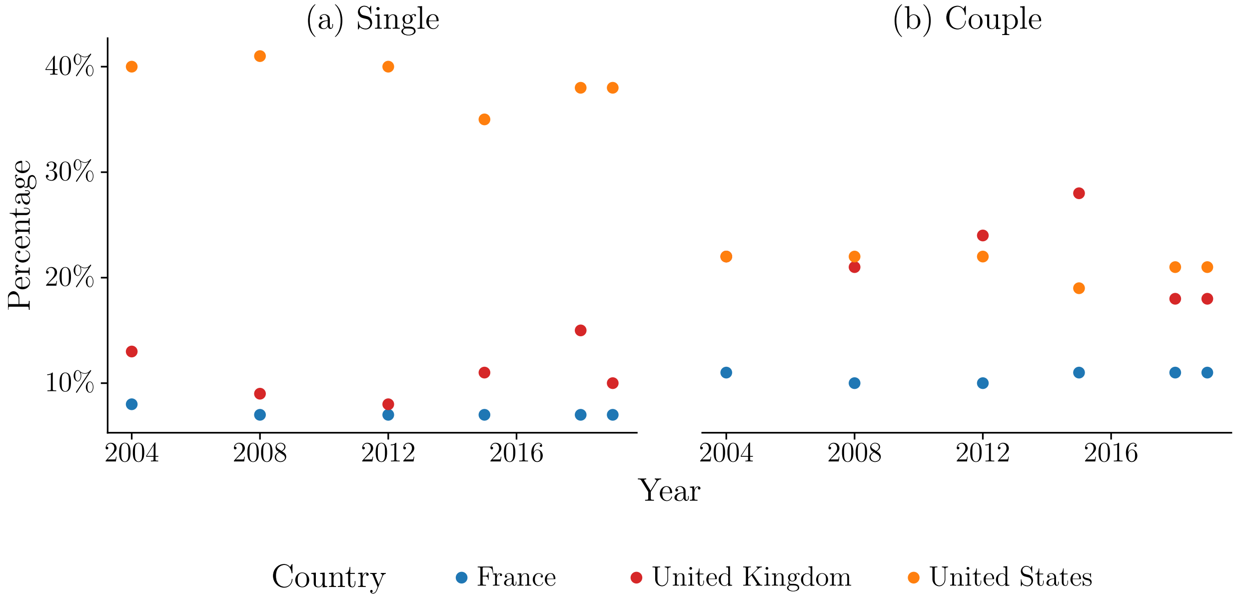
Notes: The figure plots times series of labor force participation rates for France, the United Kingdom and the United States at the yearly level. The labour force participation rates is calculated as the labour force divided by the total working-age population, separately for the men (panel (a)) and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

Figure B.4: Share of employed in part-time employment, by sex



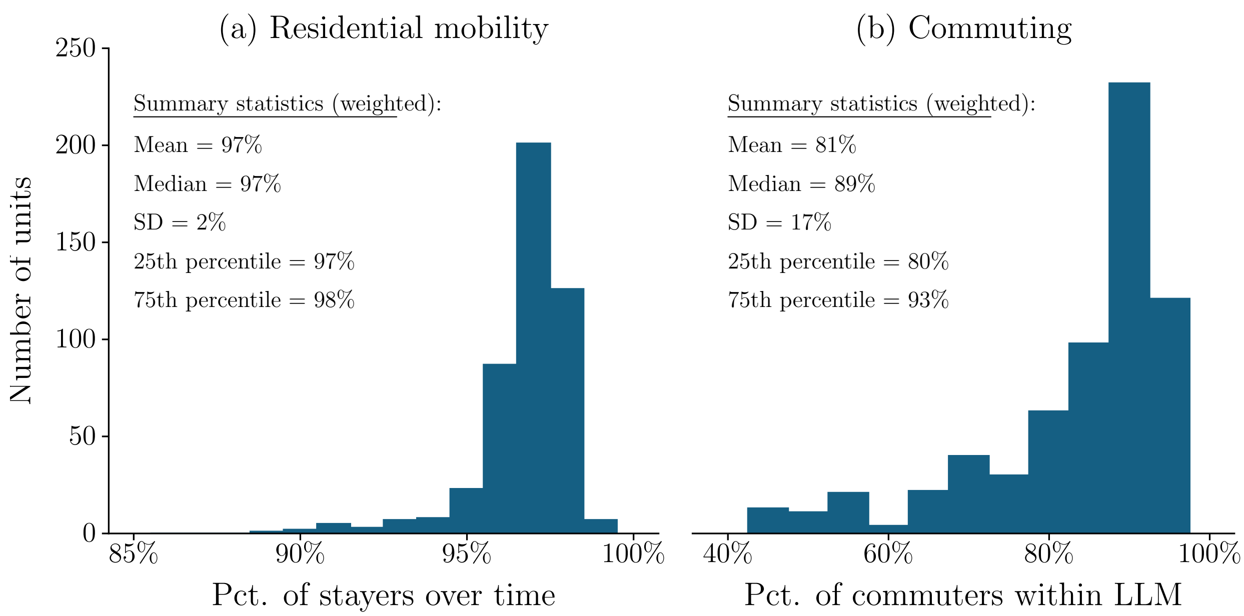
Notes: The figure plots times series of labor force participation rates for France, the United Kingdom and the United States at the yearly level. Part-time employment is defined as people in employment (whether employees or self-employed) who usually work less than 30 hours per week in their main job. 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.5: Childcare costs in net household income for parents with two children



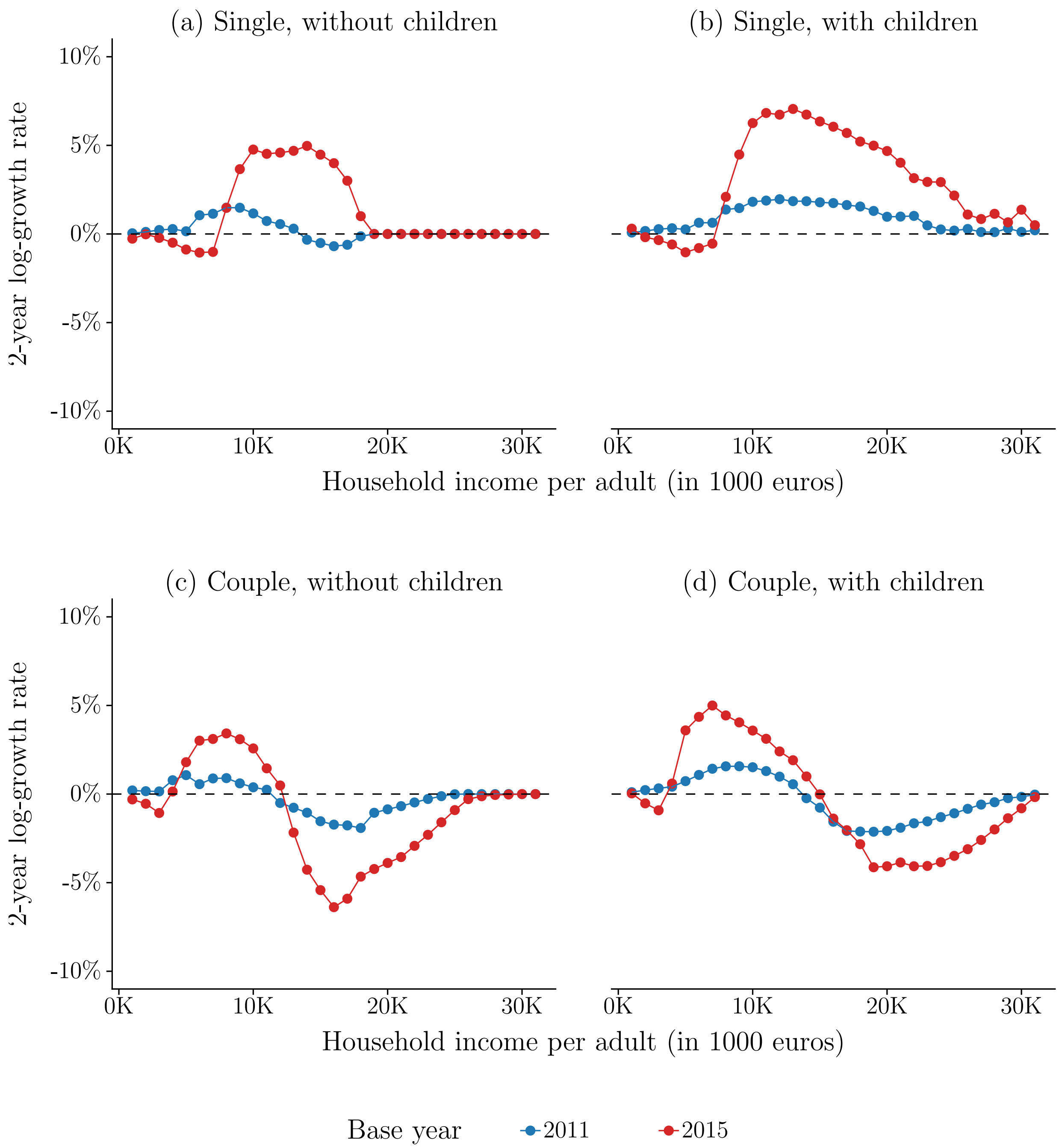
Notes: The figure plots times series of net childcare costs in percentage of net household income for France, the United Kingdom and the United States at the yearly level. Parents earn the average wage at full-time work. The net childcare cost is the difference between the gross childcare fee and childcare 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.6: Local labor markets mobility patterns



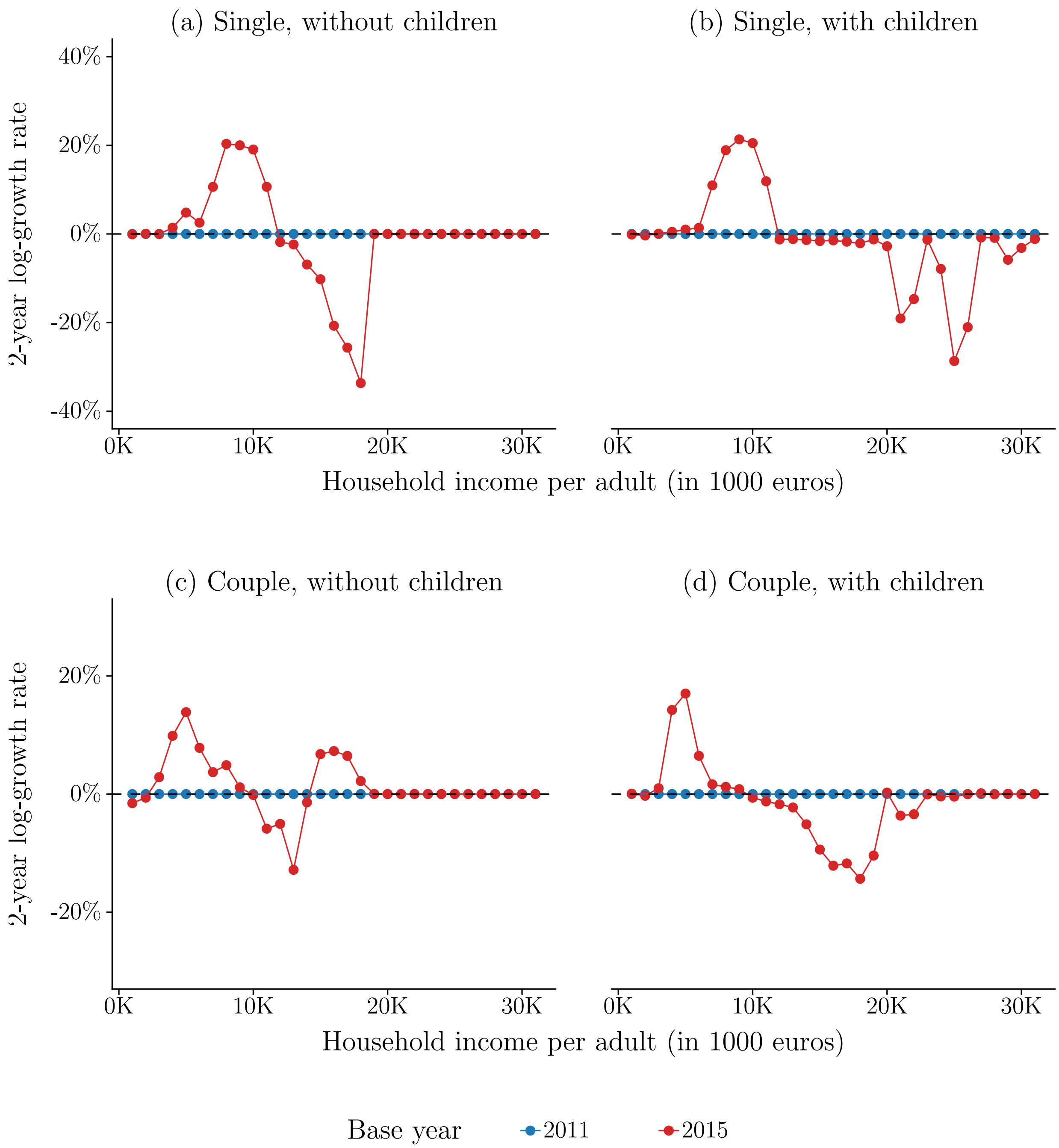
Notes: The figure describes local labor markets (LLM) mobility patterns. A unit is a defined as a local labor market $\times$ year combination. Panel (a) plots the histogram for the percentage of individuals living in the same local labor market between two periods of time (t and $t+2$). The data is main sample used in the paper and described in Section 4. Panel (b) plots the histogram for the percentage of commuters living and working in the same local labor market in a given year. The data is from the census and applies similar restrictions on demographic variables than in the main sample. Both panels reports summary statistics, weighted by the share of each local labor market in the national observed population.

Figure B.7: $\Delta^{sim} \ln(1 - \text{ATR}_{g,t})$ by treatment group, for base year 2011 and 2015 and with only wage subsidies



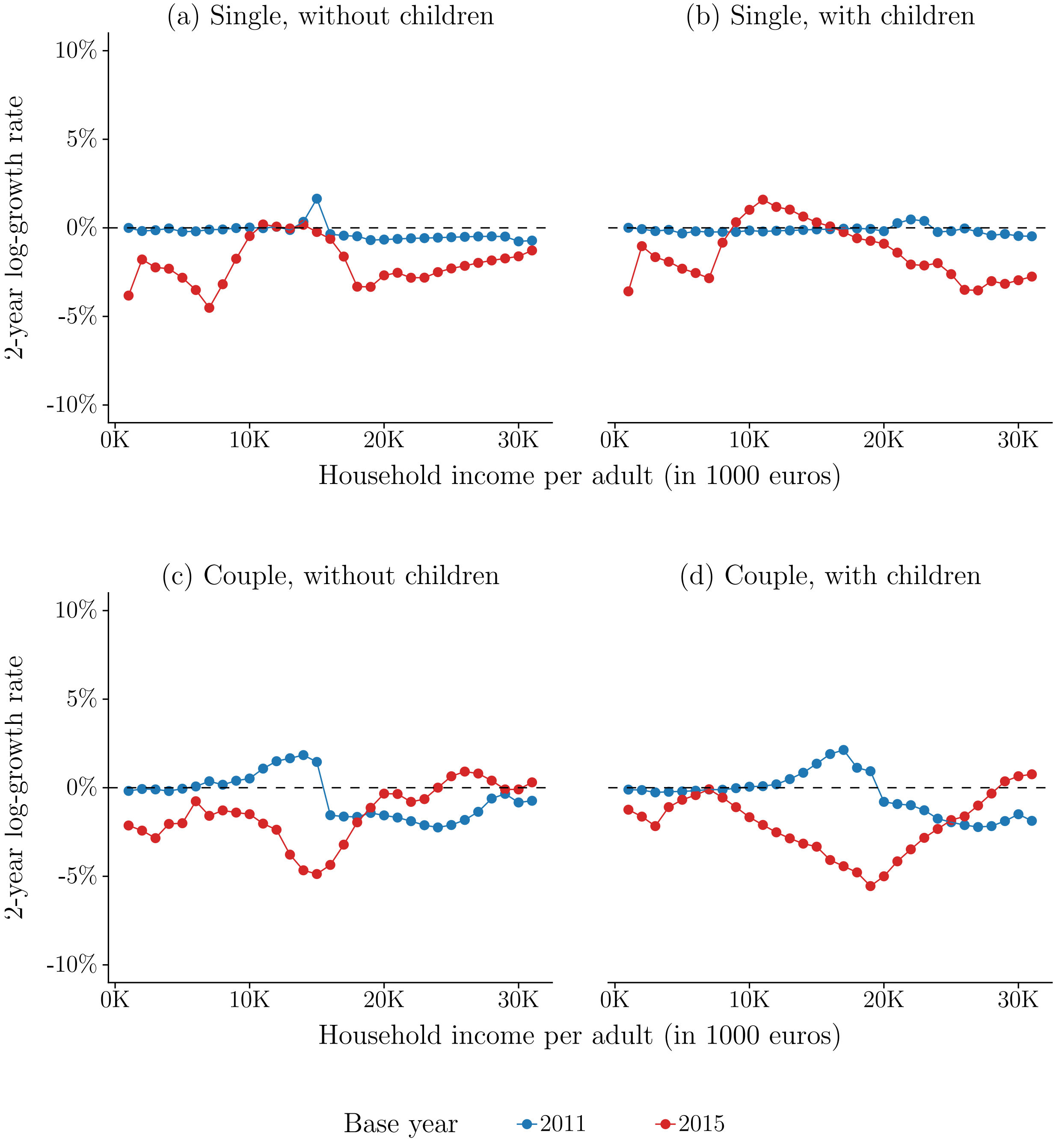
Notes: The figure plots the two-year change in the log of the participation tax rate at the treatment group-level, for base year 2011 and 2015 and considering only wage subsidies. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis).

Figure B.8: $\Delta^{sim}\ln(1-\text{MTR}_{g,t})$ by treatment group, for base year 2011 and 2015 and with only wage subsidies



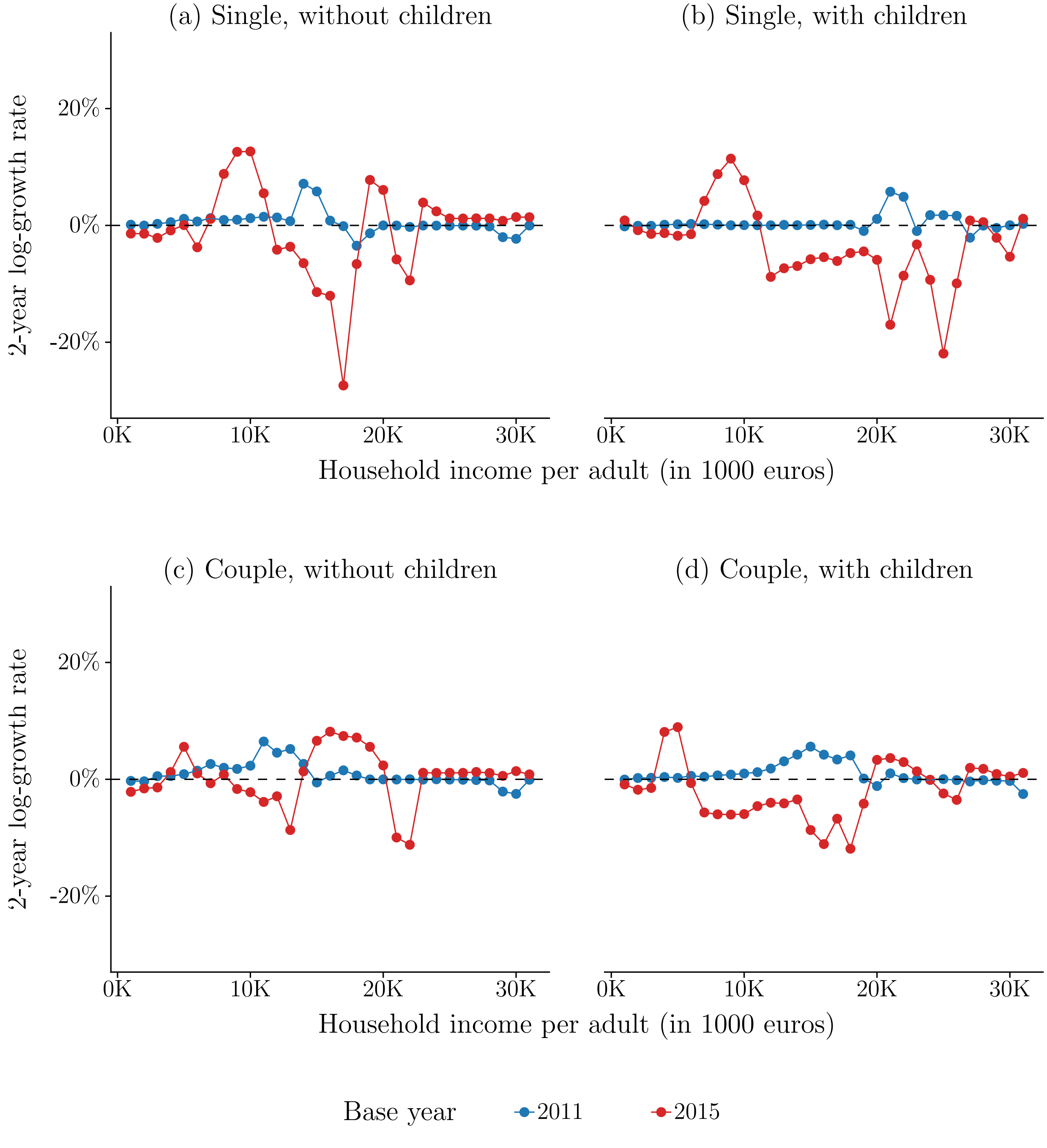
Notes: The figure plots the two-year change in the log of the net-of-tax rate at the treatment group-level, for base year 2011 and 2015 and considering only wage subsidies. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis).

Figure B.9: $\Delta \ln(1\text{-ATR}^{sim})$ by treatment group, for base year 2011 and 2015 and using the alternative definition



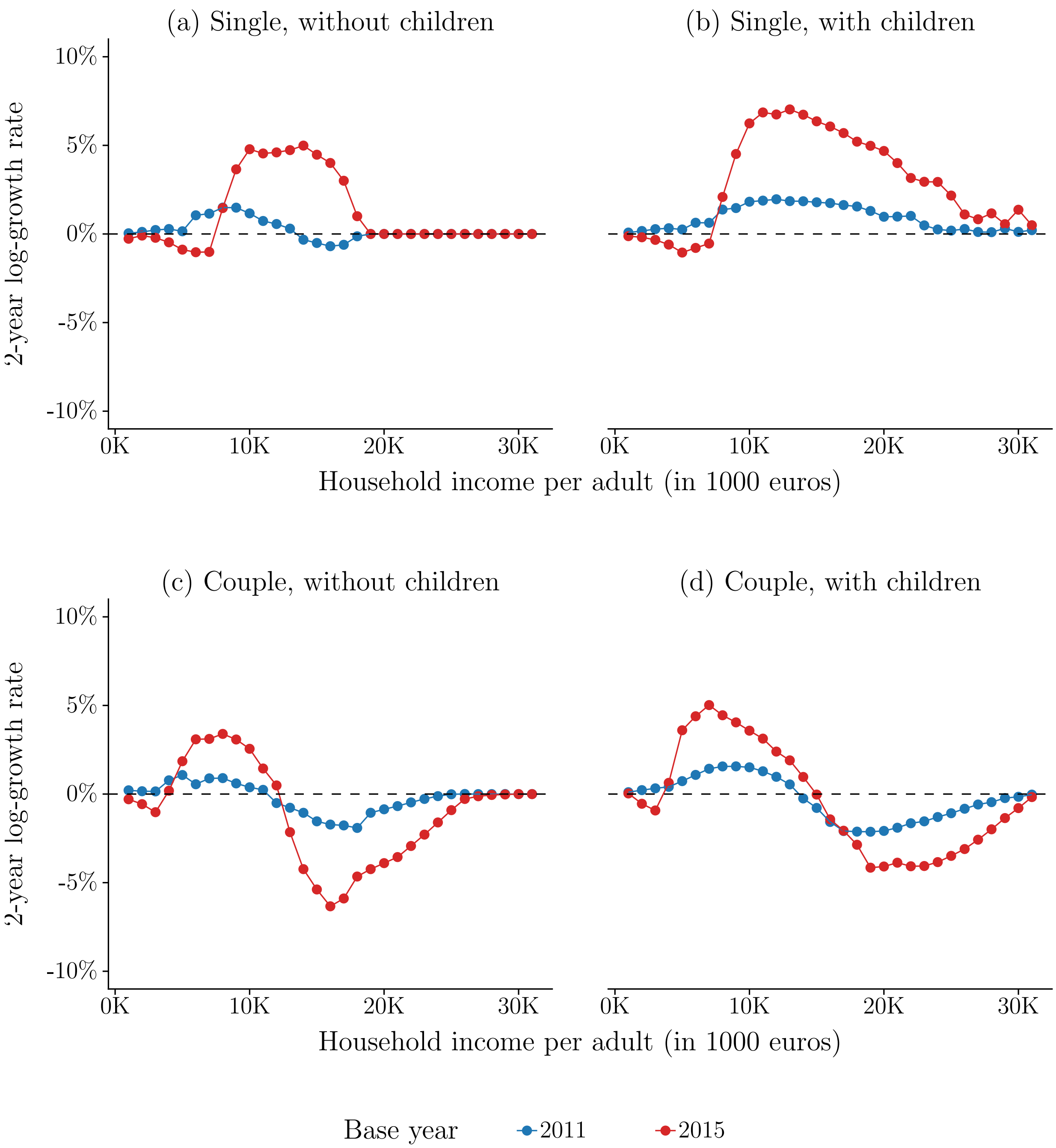
Notes: The figure plots the two-year change in the log of the participation tax rate at the treatment group-level, for base year 2011 and 2015 and considering the full tax and redistribution system. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (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). Variables are constructed using cross-sectional administrative weights.

Figure B.10: $\Delta \ln(1\text{-MTR}^{sim})$ by treatment group, for base year 2011 and 2015 and using the alternative definition



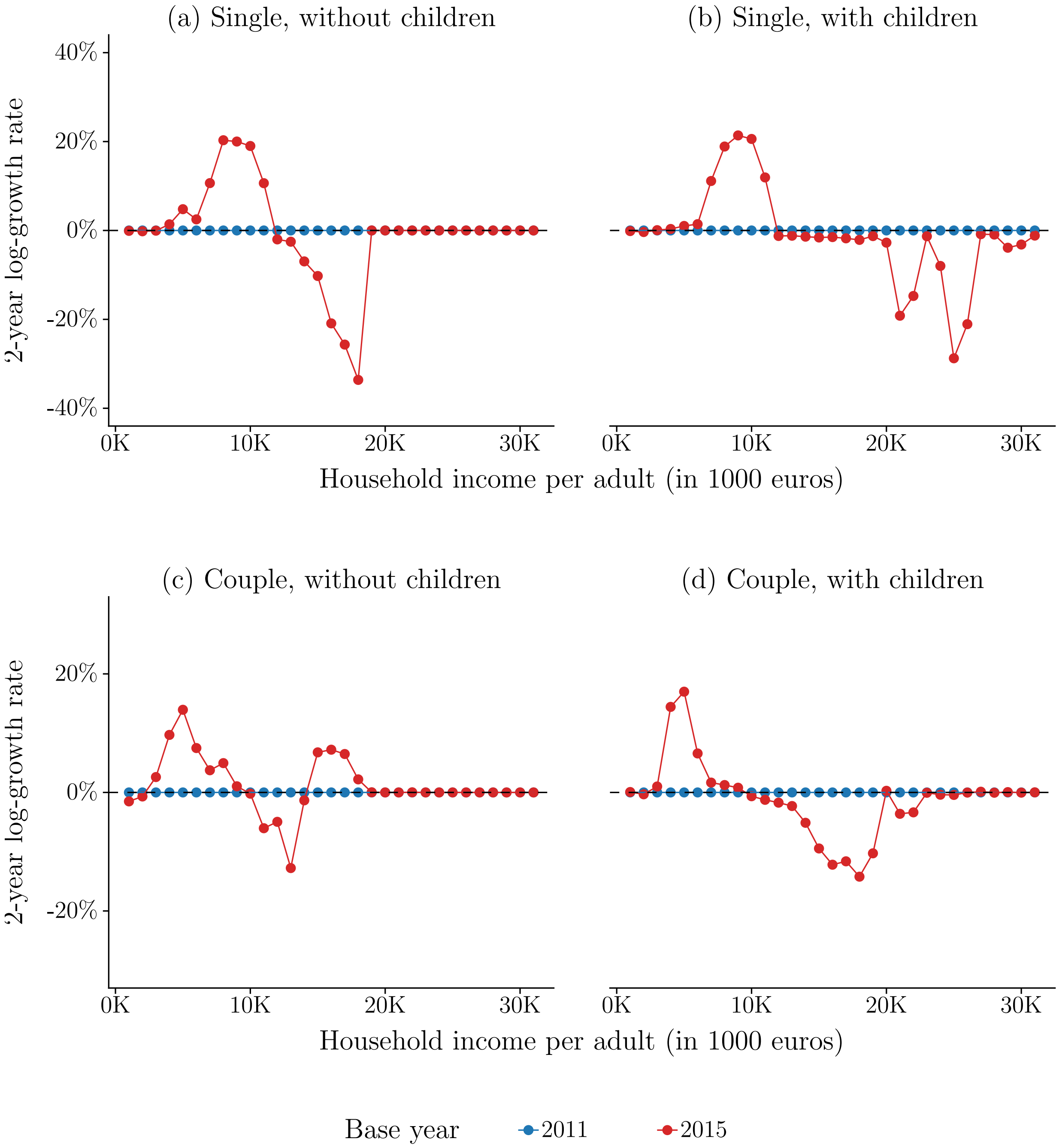
Notes: The figure plots the two-year change in the log of the net-of-tax rate at the treatment group-level, for base year 2011 and 2015 and considering the full tax and redistribution system. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis). Variables are constructed using cross-sectional administrative weights.

Figure B.11: $\Delta \ln(1\text{-ATR}^{sim})$ by treatment group, for base year 2011 and 2015, with only wage subsidies and using the alternative definition



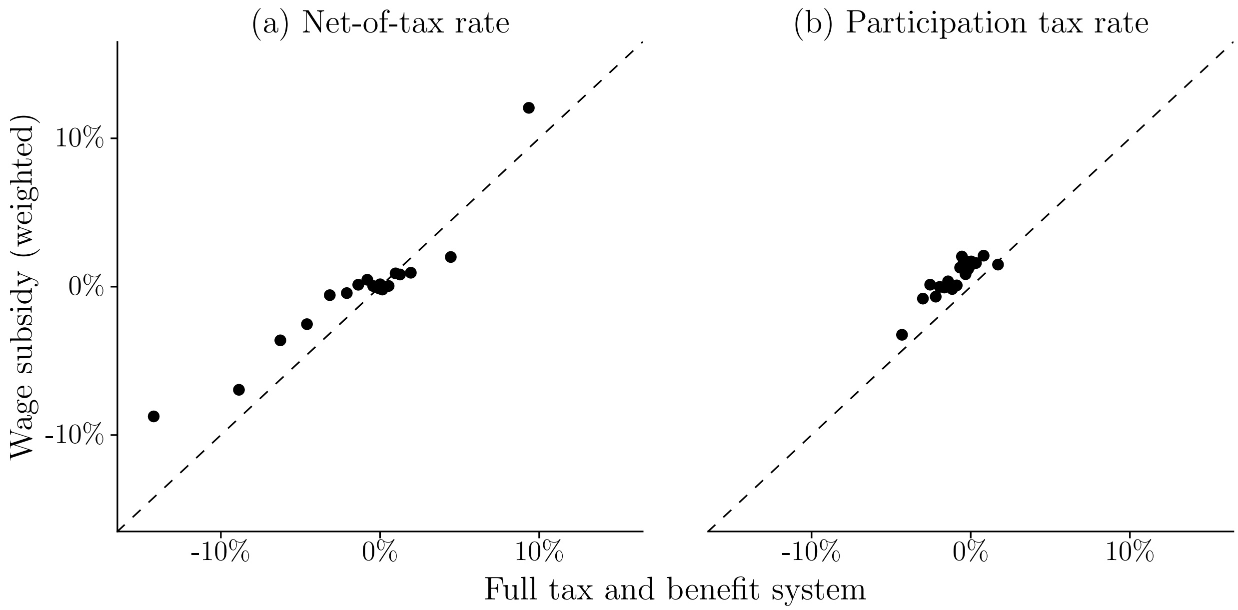
Notes: The figure plots the two-year change in the log of the participation tax rate at the treatment group-level, for base year 2011 and 2015 and considering only wage subsidies. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis). Variables are constructed using cross-sectional administrative weights.

Figure B.12: $\Delta \ln(1\text{-MTR}^{sim})$ by treatment group, for base year 2011 and 2015, with only wage subsidies and using the alternative definition



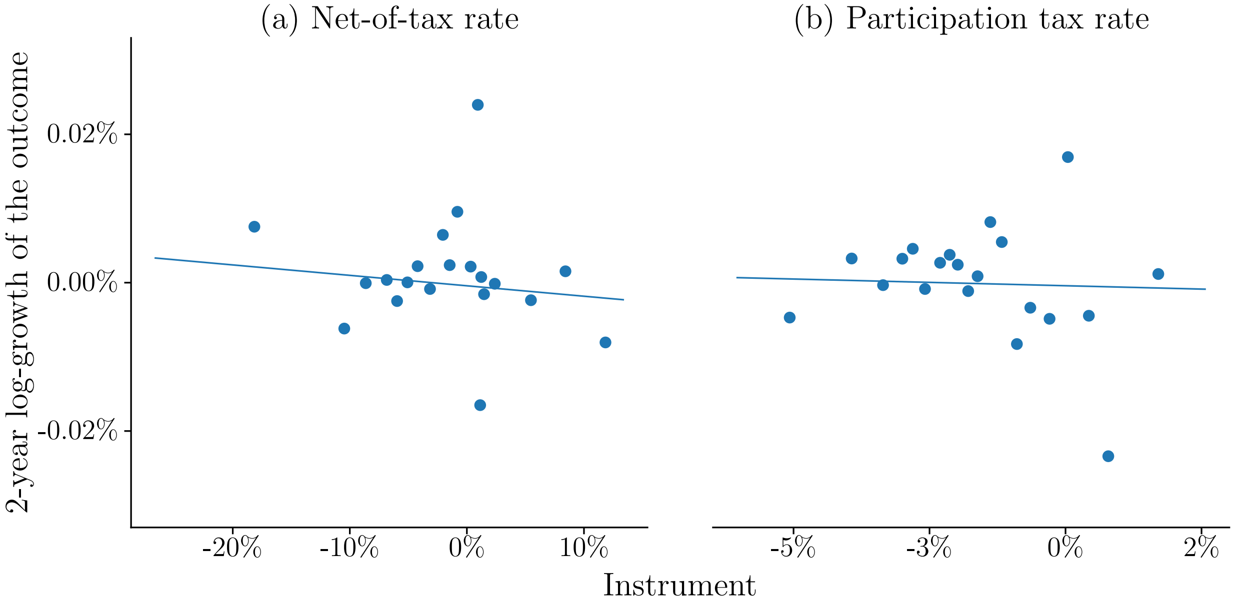
Notes: The figure plots the two-year change in the log of the net-of-tax rate at the treatment group-level, for base year 2011 and 2015 and considering only wage subsidies. The tax groups are defined by the combination of being single (panel (a) and (b)) or in a couple (panel (c) and (d)), having children (panel (a) and (c)) or not (panel (c) and (d)) and the household income per adult in euros (x-axis). Variables are constructed using cross-sectional administrative weights.

Figure B.13: Correlation between simulated tax shocks at the treatment group level



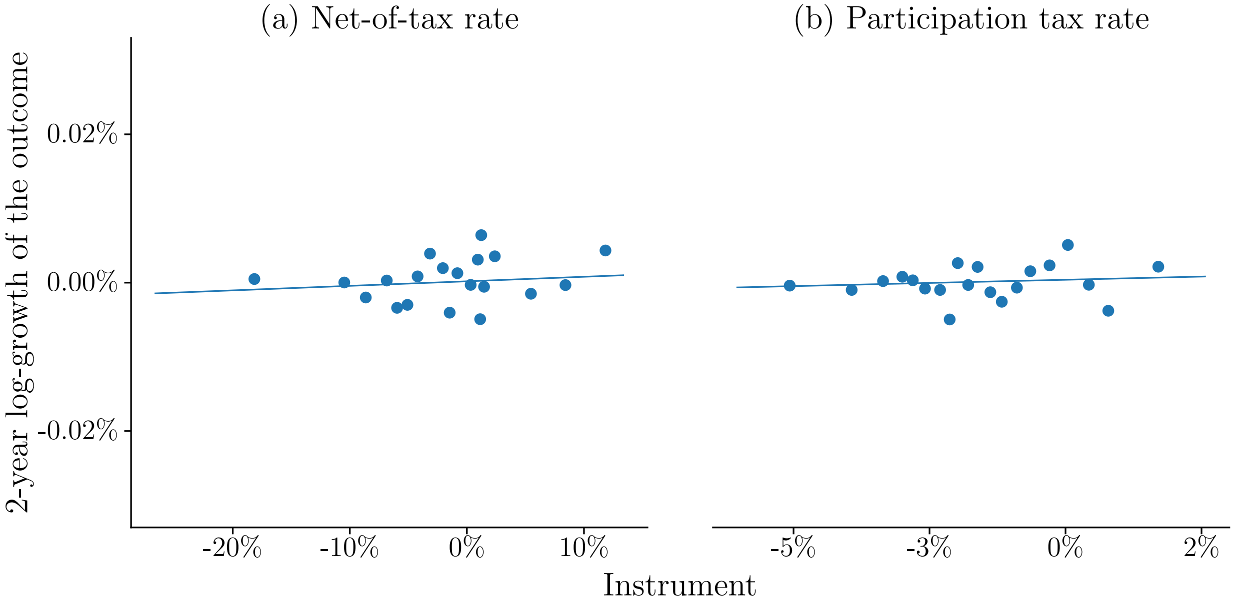
Notes: The figure plots the correlation between the two-year change in tax shocks only considering the wage subsidies (y-axis) and the full tax and benefit system (x-axis) at the treatment group-level, pooling all years together. Results are reported separately for the net-of-tax rate (panel (a)) and the participation tax rate (panel (b)). Log-growth in wage subsidies in weighted by their share in the total taxes and benefits in the initial year. Each dot represents 5% of the data. Results from an OLS regression (with intercept) reports a correlation coefficient of 0.80 for the net-of-tax rate and of 0.77 for the participation tax rate. The 45-degree line is dashed.

Figure B.14: Reduced-form employment falsification tests



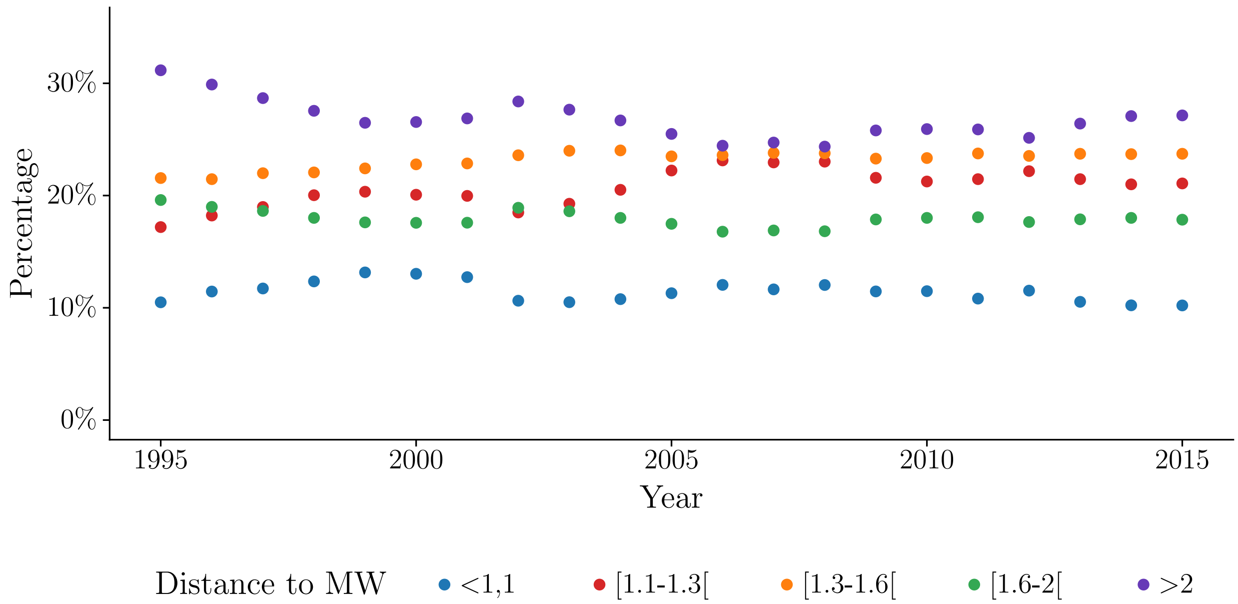
Notes: The figure plots the falsification tests for the two-year change in the log of hours at the labor market level. The two tax shocks are the two-year change in the log of the participation tax rate and net-of-tax rate. Outcomes are the change in number of hours 3 years before the shocks. Panel (a) shows the correlations with respect to the net-of-tax rate and panel (b) shows the correlations with respect to the participation tax rate. Outcomes are first residualized on a set of labor market fixed-effects, year fixed-effects, a set of socio-economic characteristics in the initial year and the other tax shock. The corresponding regression is weighted by the average treatment group exposure share $S_{g,t}$. The x-axis shows the shock size (simulated instruments) and the y-axis the average change in outcome. Each dot represents 5% of the data.

Figure B.15: Reduced-form wage falsification tests



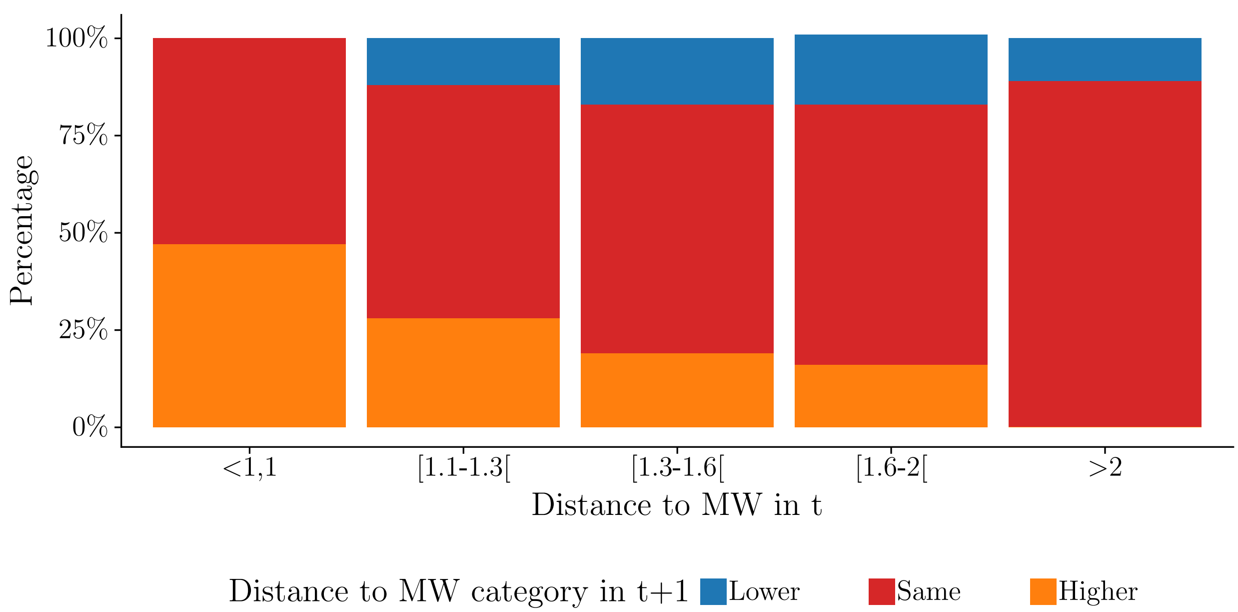
Notes: The figure plots the falsification tests for the two-year change in the log hourly wage at the labor market level. The two tax shocks are the two-year change in the log of the participation tax rate and net-of-tax rate. Outcomes are the change in number of hours 3 years before the shocks. Panel (a) shows the correlations with respect to the net-of-tax rate and panel (b) shows the correlations with respect to the participation tax rate. Outcomes are first residualized on a set of labor market fixed-effects, year fixed-effects, a set of socio-economic characteristics in the initial year and the other tax shock. The corresponding regression is weighted by the average treatment group exposure share $S_{g,t}$. The x-axis shows the shock size (simulated instruments) and the y-axis the average change in outcome. Each dot represents 5% of the data.

Figure B.16: Distribution of the distance to the minimum wage over time



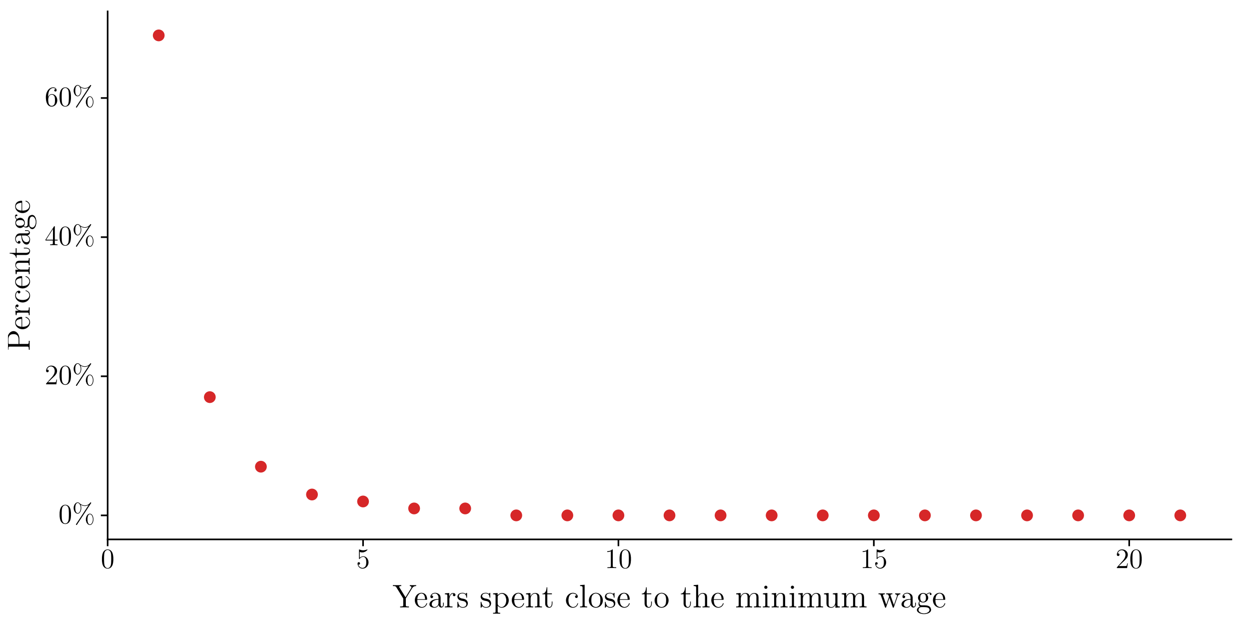
Notes: The figure plots the percentage of the salaried population in bins of distance to the minimum wage over time. Data and methodology is available here.

Figure B.17: Transition between distances to the minimum wage



Notes: The figure plots the transition rates between bins of distance to the minimum wage between two consecutive years. Data and methodology is available here.

Figure B.18: Years spent close to the minimum wage



Notes: The figure plots the distribution of years spent close to the minimum wage, as defined by being below 1.1 times the minimum wage, conditional on starting a period at the minimum wage. Data and methodology is available here.

C Data and Variable Construction

C.1 Data

The primary dataset used in this study is the *Echantillon Démographique Permanent* (EDP), a 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's important to note that the EDP not only collects individual-level variables on the sampled individuals, but also individual-level variables of other members of the household 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 provides extensive details about individuals' demographics, including their birth and death dates, place 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 as 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, this data helps defining individuals' places of residence.

C.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.

C.2.1 Step 1: selection of the population

I begin by selecting the population for each year independently, focusing solely on the cross-sectional aspect of the data. For the years spanning from 2011 to 2017, 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, individuals with a place of residence outside the French metropolitan area, and those aged between 25 and 55 years.

For years prior to 2011 (inclusive), I exclude individuals who entered into marriage/civil union within the year. This is because 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 in civil unions or are married. For the years from 2011 to 2017, I also exclude individuals who went through divorce or experienced the death of their spouse for similar reasons.

Subsequently, 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 tax household definition 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 that 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.

Lastly, 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, and foreign incomes.

C.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 a tax and benefit simulator designed for the French tax and benefit system. Openfisca is accessible online and is implemented using Python.

Before the simulation procedure, I first estimate the counterfactual labor earnings for individuals who did not work at all in a specific year and thus reported zero labor earnings. I provide a comprehensive explanation of this procedure in the appendix, specifically in subsection C.3.

Openfisca requires several variables regarding incomes and socio-economic characteristics at both the individual-level and household-level. At the individual level, I provide data on marital status (single, divorced, widowed, civil union, married), labor earnings (including a counterfactual equivalent 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, and information on received housing benefits, along with the city of residence as an input.

It's worth noting that treating housing benefits as a constant in the calculation of marginal and average tax rates represents a strong assumption, as these benefits can partially depend on income. Unfortunately, I lack data on rent payments, which is essential for accurately computing housing benefits. Consequently, I make the assumption that housing benefits do not significantly influence the determination of marginal and average tax rates.

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's 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 utilization at the annual level.

Finally, I compute two sets of marginal and average tax rates. The first set considers the full tax and benefit system, while the second set focuses solely on the wage subsidies. You can find the exact formulas in subsection C.3.

C.2.3 Step 3: construction of the estimation samples

At this point, I narrow my focus to individuals within the sample who are sampled and have a unique consistent identifier. I retain observations based on the consistency between observed net labor earnings and taxable labor earnings, as taxable labor earnings should typically exceed net earnings due to the inclusion of non-deductible social contributions. I maintain records for individuals with non-zero labor earnings that meet this condition, as well as individuals with zero labor earnings. All monetary values are presented in real terms, with a base year of 2011.

Next, I create two versions of the dataset. First, I establish a cross-sectional version that is used for share construction to maximize the sample size and ensure a representative distribution of individuals across labor markets and treatment groups. I retain individuals with an hourly wage strictly below 14 euros in this version.

Second, I create a panel version of the data by matching variables from year t to year $t - h$ for each individual observed in both periods. In my baseline analysis, I set $h = 2$, which allows me to generate two sets of individual-level shocks: changes in tax rates with respect to the wage subsidy (weighted by the initial share of the wage subsidy in total taxes and benefits) and changes in tax rates with respect to the full tax and benefit system. subsection C.3 presents the precise formulas. In this panel version, I retain individuals with an hourly wage strictly below 14 euros in year $t - h$.

C.2.4 Step 4: data aggregation and binning

In the final step, I aggregate the shocks at the labor market level, denoted by m, and year level, denoted by t. To achieve this, I create three sets of variables. First, the log growth between year t and $t - h$ for various outcomes (hourly wage rate, number of hours worked, total labor earnings), represented as $\Delta \ln(Y_{m,t})$. Second, the share of individuals in treatment group g in the total labor supply at the market level in year t, denoted as $S_{m,g,t}$. Third, the logarithmic growth in the net-of-tax rate and participation tax rate at the treatment group level between year t and $t-h$.

Detailed information about the construction of these variables are available in subsection C.3.

C.3 Variable Construction

C.3.1 Counterfactual labor earnings

To classify households into treatment groups accurately, I need information about their labor earnings. However, for individuals who report zero earnings within a given year, it's 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's important to note that I estimate the counterfactual labor earnings only for individuals with a unique identifier over time, i.e. excluding spouses, for whom this estimation is not applicable.

I follow a similar procedure as kleven2019eitc. I start by estimating the relationship between the log of labor earnings $\ln(Y_i)$ and a set of fixed-effects, conditional on having positive earnings. The estimation is done on the cross-sectional version of the data to maximize sample size, and separately for each year:

$$\ln(Y_i) = \alpha_{sex} + \alpha_{ms} + \alpha_{age} + \alpha_{res} + \lambda_{sex,ms} + \lambda_{sex,age} + \lambda_{ms,age} + \lambda_{res,sex} + \lambda_{res,ms} + \lambda_{res,age} + \epsilon_i$$

where *sex* is a categorical variable for men/women, *ms* is a categorical variable for the marital status (single/divorced/widowed/civil union/married), *res* is a categorical variable for the place of residence based on the French *departements* (local labor markets) and *age* is a categorical variable containing the age of individuals. The estimated coefficients are used to predict labor earnings for the non-working population: $\exp\left(\widehat{\ln(Y_i)}\right)$.

Finally, I follow the same procedure for the number of hours worked and the hourly wage rate.

C.3.2 Tax rates

For simplicity, I omit the local labor market index m and the treatment group index g.

Marginal tax rate To compute marginal tax rates, I perform a two-step simulation of the tax system. First, I simulate the tax system using observed individual and household values. Then, I conduct a second simulation by adding 100 euros to labor earnings for the sampled individuals while keeping all other variables constant. I define the simulated marginal tax rate using the following formula:

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

where $y_{i,t}$ is the labor earnings for individuals i in year t. I apply directly this formula for the wage subsidy, but use an alternative formulation for the marginal tax rate with respect to the full tax and benefit system:

$$\text{MTR}_{i,t}(y_{i,t}) = 1 - \frac{Z_{i,t}(y_{i,t} + 100, \cdot) - Z_{i,t}(y_{i,t}, \cdot)}{100}$$

where $Z_{i,t}$ is the disposable income. The equivalence with the previous formula comes from $T_{i,t}(y_{i,t}) = R_{i,t}(y_{i,t}) - Z_{i,t}(y_{i,t})$ and $T_{i,t}(y_{i,t} + 100) = R_{i,t}(y_{i,t} + 100) - Z_{i,t}(y_{i,t} + 100) = R_{i,t}(y_{i,t}) + 100 - Z_{i,t}(y_{i,t} + 100)$, with $R_{i,t}$ the pre-redistribution income.

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

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

where $y_{i,t-h}$ 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 Average tax rates are computed by simulating the tax system twice. First, with the observed individual and household values. Second, by considering labor earnings equal to zero for sampled individuals. I define the simulated tax rate using the following formula:

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

where $y_{i,t}$ is the labor earnings for individuals i in year t. I apply directly this formula for the wage subsidy, but use an alternative formulation for the average tax rate with respect to the full tax and benefit system:

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

where $Z_{i,t}$ is the disposable income. The equivalence with the previous formula comes from $T_{i,t}(y_{i,t}) = R_{i,t}(y_{i,t}) - Z_{i,t}(y_{i,t}) = R_{i,t}(0) + y_{i,t} - Z_{i,t}(y_{i,t})$ and $T_{i,t}(0) = R_{i,t}(0) - Z_{i,t}(0)$, with $R_{i,t}$ the pre-redistribution income.

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

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

where $y_{i,t-h}$ is the labor earnings for individuals i in year $t-h, h > 0$. All incomes 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.

C.3.3 Individual-level shocks

I compute the log-growth in net-of-tax and participation tax rates at the individual-level (indexed by i) for two sets of variables: with respect to the full tax and benefit system and with respect to the wage subsidy. I explain below the construction for the observed shocks, but the procedure remains the same for the simulated instruments. For simplicity, I omit the local labor market index m and the treatment group index g.

Full tax and benefit system The log-growth of the net-of tax rate is defined as follows:

$$\Delta \ln\Big(1 - \mathrm{MTR}_{i,t}^{full}\Big) = \ln\left(\frac{1 - \mathrm{MTR}_{i,t}^{full}}{1 - \mathrm{MTR}_{i,t-h}^{full}}\right)$$

where $\mathrm{MTR}_{i,t}^{full}$ is the marginal tax rate in year t. The log-growth rate of the participation tax rate is defined by:

$$\Delta \ln\Big(1 - \mathrm{ATR}_{i,t}^{full}\Big) = \ln\left(\frac{1 - \mathrm{ATR}_{i,t}^{full}}{1 - \mathrm{ATR}_{i,t-h}^{full}}\right)$$

where $\mathrm{ATR}_{i,t}^{full}$ is the average tax rate in year t.

Wage subsidy The log-growth of the net-of tax rate is defined as follows:

$$\Delta \ln\big(1 - \mathrm{MTR}_{i,t}^{ws}\big) = \ln\left(\frac{1 - \mathrm{MTR}_{i,t}^{ws}}{1 - \mathrm{MTR}_{i,t-h}^{ws}}\right) \times \frac{1 - \mathrm{MTR}_{i,t-h}^{ws}}{1 - \mathrm{MTR}_{i,t-h}^{full}}$$

where $\mathrm{MTR}_{i,t}^{ws}$ is the marginal tax rate in year t. It is weighted by the share of the marginal tax rate with respected to the wage subsidy in the full tax and benefit marginal tax rate, such that $\sum_k \Delta \ln\big(1 - \mathrm{MTR}_{i,t}^{k}\big) = \Delta \ln\Big(1 - \mathrm{MTR}_{i,t}^{full}\Big)$. The same logic applies for the log-growth of the participation tax rate:

$$\Delta \ln\big(1 - \mathrm{ATR}_{i,t}^{ws}\big) = \ln\left(\frac{1 - \mathrm{ATR}_{i,t}^{ws}}{1 - \mathrm{ATR}_{i,t-h}^{ws}}\right) \times \frac{1 - \mathrm{ATR}_{i,t-h}^{ws}}{1 - \mathrm{ATR}_{i,t-h}^{full}}$$

C.3.4 Shares

To obtain $S_{m,g,t}$, the share of treatment group g in total labor supply of labor market m in year t (omitting the treatment group index g for simplicity), I use the cross-section of the data. For each year, I use the following formula:

$$S_{m,g,t} = \frac{L_{m,g,t}}{L_{m,t}} = \frac{\sum_i a_{i,m,g,t} h_{i,m,g,t}}{\sum_g \sum_i a_{i,m,g,t} h_{i,m,g,t}}$$

where $h_{i,m,g,t}$ is the number of hours worked by individual i and $a_{i,m,g,t}$ is an administrative (frequency) weight for the sample to be nationally representative. I winsorize the top 1% of the distribution of $h_{i,m,t}$. My main analysis does not use the cross-sectional sample weights, such that $a_{i,m,g,t} = 1$ for all individual-level observations.

C.3.5 Outcomes

I have three outcomes in this paper at the labor market level m: the log-growth in the hourly wage rate, the log-growth in the total number of hours worked and the log-growth in total earnings. I use the panel data version of the sample to compute them. Note that my main analysis does not use the cross-sectional sample weights, such that $a_{i,m,g,t} = 1$ for all individual-level observations.

I start with the definition of the change in employment by taking the log-growth rate of the total number of hours worked in a given labor market:

$$\Delta \ln(L_{m,t}) = \ln\left(\sum_i a_{i,m,g,t} h_{i,m,t}\right) - \ln\left(\sum_i a_{i,m,g,t-h} h_{i,m,t-h}\right)$$

with $h_{i,m,t}$ the number of hours worked for individuals i in year t. Note that labor market m is defined in $t-h$ and kept fixed for t. I winsorize the top 1% of the distribution for both $h_{i,m,t}$ and $h_{i,m,t-h}$ by initial year $t-h$ to avoid extreme values.

Then, I construct a measure of wage rate by computing the hours-weighted wage rate.

Formally, this measure for a given labor market in a given year is given by:

$$w_{m,t} = (\sum_i a_{i,m,t} w_{i,m,t} h_{i,m,t}) / (\sum_i a_{i,m,t} h_{i,m,t})$$

with $w_{i,m,t}$ the hourly wage rate and $h_{i,m,t}$ the number of hours workerd by individual i. Then, I take the log-growth rate of the total number of hours worked in a given labor market:

$$\Delta \ln(w_{m,t}) = \ln(w_{m,t}) - \ln(w_{m,t-h})$$

where I winsorize the bottom 1% of the distribution for both $w_{i,m,t}$ and $w_{i,m,t-h}$ by initial year $t-h$ to avoid extreme values.

Finally, I compute the log-growth in total earnings at the labor market level as follows:

$$\Delta \ln(w_{m,t} L_{m,t}) = \Delta \ln(L_{m,t}) + \Delta \ln(w_{m,t})$$

taking into account the winsorization on the hourly wage and number of hours described above.

C.3.6 Treatment group-level shocks

The goal is to compute the average log-growth for the net-of-tax and participation tax rates at the treatment group-level g. Consider the shock $\theta_{g,t}$. It is a hours-weighted aggregation of the shocks at the individual level:

$$\theta_{g,t} = \sum_i \frac{a_{i,g,t-h} h_{i,g,t-h}}{\sum_i a_{i,g,t-h} h_{i,g,t-h}} \times \theta_{i,g,t}$$

where $h_{i,g,t-h} / \sum_i h_{i,g,t-h}$ is the share of hours worked by individual i in the treatment group total number of hours in the initial year $t-h$. Note that consistent with the construction of outcomes, I winsorize the top 1% of the distribution for both $h_{i,g,t-h}$ by initial year $t-h$

to avoid extreme values. For similar reasons, I winsorize the top 5% and bottom 5% of the distribution of shocks by initial year $t-h$.

I follow the same procedure to construct the instruments at the treatment group-level, replacing the observed shock $\theta_{i,g,t}$ by the simulated instruments $\theta^{sim}_{i,g,t}$. My main analysis does not use the cross-sectional sample weights, such that $a_{i,m,g,t}=1$ for all individual-level observations.