Working hours policy reform: micro and macro impacts*

Preliminary and Incomplete

Mauricio Tejada
Department of Economics, Universidad Diego Portales and LM^2C^2

Benjamín Villena-Roldán
Institute for Economic Policies, Universidad Andres Bello, LM^2C^2, and MIPP.

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Abstract

We use microdata surveys to study the impact of the law approved in 2001 announcing a reduction of legal hours in 2005 in Chile. Using a difference-in-difference approach, we find non-significant and mild anticipated negative impacts on private employment, but mostly non-significant effects for directly affected workers at the implementation in 2005. Taking into account likely general equilibrium effects, we assess the macro effect of this policy change by constructing a synthetic panel and estimating local projections. We find a large increase in self-employment that offsets a drop in salaried private employment to generate a positive effect on total employment. These findings may shade some light on the current debate on reducing working hours in several countries.

To rationalize our empirical results, we construct a search and matching model of the labor market in which both wages and hours are bargained. The maximum legal hours act as a side constraint in the bargaining game. Additionally, the model includes a flexible type of employment, self-employment, for which legal hours are not

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a constraint. We structurally estimate the model using data from Chile. Performing a counterfactual experiment in which the legal hours change, we find results similar to those implied by the local projection approach: namely, a small increase in total employment, a reduction in full-time employment, and an increase in self-employment. Furthermore, because changes in legal hours affect the outside option of workers (the equilibrium effect), the matching rate between workers and jobs is also affected, resulting in longer unemployment durations.

Keywords: Legal hours worked, Employment, Policy evaluation, Difference-in-difference, Local projections.

JEL Codes: J08, J22, E24, C21, C32.

1 Introduction

Time allocation is a key household decision that has a first-order impact on welfare. There is a well-known long-run relationship between hours worked and income level, with multiple competing explanations.[1]. Despite several endogenous mechanisms for the decay of hours worked, an increasingly relevant factor driving this fact is legal hours regulations, which are present in many economies, such as France, Portugal, Germany, and recently Spain. In Latin America, besides Chile, Ecuador, Colombia, and Brazil have implemented a legal hours reduction at different points in time.

After the reduction in legal hours worked in the 1990s in Portugal and France, probably the two economies most researched in this regard, there is a resurgence of debate on regulating working time in the form of reducing the workweek from 5 to 4 days in the dissemination (Gomes, 2021) and academic literature (Campbell, 2024), also influenced by the increasing prevalence of shorter workweeks in the US and other countries (Hamermesh and Biddle, 2025). However, much of the impact of reducing hours worked is still unknown. With respect to the literature studying the impact of hours worked, the evidence remains mixed, ranging from small negative effects on employment to negligible, or even large positive impacts in the context of the Great Depression (Fishback et al., 2024). However, these reforms were jointly implemented with compensation and flexibilization regulations to ameliorate the foreseen negative effects of the hours reduction (Chemin and Wasmer, 2009) or in highly recessive

[1] Boppart and Krusell (2020) rationalize this fact by an income effect stronger than a substitution effect for labor supply determination. Other theories propose the reduction in fixed costs and sectoral reallocation to explain time-use trends as an important mechanism (Bick et al., 2022). Yet another explanation is the decline in the price of leisure goods (Kopytov et al., 2023)

situations (Fishback et al., 2024). With respect to the "novel" debate on workweek reduction, Cuello (2023) argues that the pilots implemented are poorly designed and have questionable scalability. To some extent, the latter critique could be extended, in some sense, to many academic empirical evaluations in which general equilibrium effects are not considered.

In 2005, the Chilean law mandated a reduction in the maximum number of hours worked per week from 48 to 45. If this number of hours is exceeded, the employer must pay an additional 50% for each hour worked. This is a cleaner "natural experiment" as it just reduced the hours in the workweek but also entails an increase in hourly wages, as the law mandated frozen nominal monthly wages. Sánchez (2013) studies the anticipation effect of the 2005 reform, finding non-significant Average Treatment Effect on the Treated (ATET) in job separations using a difference-in-difference (DD) design.

In our paper, we make progress in evaluating the impact of this natural experiment to obtain economic and methodological 2005 Chilean reform using different and complementary empirical strategies that address two important empirical concerns that suggest that the standard DD approach may not provide useful answers in evaluating this regulatory change. First, standard DD assumes that there is no anticipation effect, something that does not hold in this case since the 2005 reform was a consequence of a law approved by Congress in 2001. A second setback is the stable unit treatment value assumption (SUTVA), which asserts that the treatment of one individual does not affect the outcome of another, does not hold in this case. We show that unless the spillover offset (SO) condition occurs, i.e. the indirect effects on the treated group and on the control group exactly cancel out, standard DD approaches would deliver biased results. Sufficient conditions for SO condition to happen are the standard parallel trends and no spillover effects. Therefore, the research assessing worked hours legal reductions solely focusing on effects over the treated workers is likely to misrepresent the actual effects of the policy change.

To illustrate these points, we first estimate the naive ATET of the 2005 legal hours reduction on those directly affected, i.e. individuals in the formal private sector working more than 46 weekly hours before 2005. To do so, we use the *Encuesta Nacional de Empleo*, ENE hereafter, which is a survey of the rotating panel with individuals in quarterly frequency. We focus on individuals whose observations lie before and after January 2005. We conduct our analysis by taking as a control group (a) individuals working less than 45 hours per week before January 2005 and (b) individuals working 40 to 45 weekly hours before January 2005. While some point estimates suggest even positive results in employment, they are non-significant at conventional levels.

In order to understand the anticipation effect of the reform announced in 2001, we use a complementary dataset, the *Encuesta de Protección Social*, EPS hereafter, a balanced panel consisting of retrospective work histories between 2002 and 2004. We estimate effects at early (2003) and late (2004) anticipation dates, finding some mild negative effects on employment. While we conduct some robustness analysis in our estimates using both EPS and ENE data, the overall picture does not change.

Nevertheless, the standard theory of frictional search and matching undoubtedly imply some spillover or general equilibrium effects of a national reform such as the Chilean one in 2001-05. In the language of the policy evaluation literature the SUTVA does not hold: the regulation not only affected those directly "treated" but also many others regarded as "control group" because the reform changes the composition and ultimately the effort of agents searching in the market, affecting their outside options.

Hence, we adopt an empirical macroeconomic approach. We construct a synthetic panel using ENE data for the period 2000-2008 to estimate the dynamic impact of the policy. To do so, we use a panel local projection approach to estimate the response of various outcome variables to a shock in hours worked over an extended period, specifically three years following the shock. We find a positive and increasing impact on total employment: the probability of being employed increases by 1.9 percentage points in response to the average reduction of 2.1 hours after two years. Conversely, wage employment, particularly in the private sector, experiences a significant decrease following the shock. The probability of being employed as a waged employee in the private sector decreases by 1 percentage point for an average reduction of 2.1 hours. This decline indicates a shift towards self-employment, which shows an increase due to the reduced opportunities in wage employment. In fact, the probability of working as self-employed increases by 1.4 percentage points for an average reduction of 2.1 hours.

Furthermore, we find that unemployment initially increases, but this trend sharply reverses, with a notable decrease over time. The duration of unemployment initially remains stable but increases significantly by the end of the first year, only to decrease as self-employment grows. This pattern suggests a tightening of the labor market, leading to diminished bargaining power for new hires and a subsequent decrease in labor income, especially in more flexible job types. These insights strongly highlight the spillover effects within the labor market following changes induced by policy.

To understand these empirical findings, we construct a structural search and matching model incorporating wage bargaining, endogenous self-employment, and endogenous hours choices within the regulated workweek framework. We estimate this model using the 2009 CASEN survey, achieving a reasonable fit for key moments under the 45-hour workweek. We then simulate the model under the pre-reform 48-hour workweek, generating predictions that can be compared to the macroeconomic evidence obtained from our local projections. The simulated 48-hour economy exhibits lower self-employment, higher market tightness, and higher job arrival rates, wages, and productivity. These differences arise from the policy's influence on outside options and the selection effects associated with endogenous self-employment and employment decisions. We also use the model to foresee the effect of a workweek reduction from 45 to 40 ours that will take place in 2028 under a recently approved Chilean law. Although we have some caveats since this reform defines an average workweek of 40 hours, instead of fixed 45, the effects align to the rationale behind the 2005 reduction in the model: higher self-employment, lower formal employment, wages, and productivity.

Our analysis reveals that traditional microeconometric approaches may mask crucial policy impacts due to its focus on causal impacts assuming away spillover effects. While our initial micro-analysis, consistent with much of the existing micro-literature, finds limited effects on directly affected workers, the aggregate data paint a significantly different picture. Our findings caution against relying solely on micro-evidence when evaluating work hour reduction policies. Our theoretical model, grounded in a mostly standard search and matching framework, highlights the substantial spillover effects of such policies. The legal workweek regulation affects not only the directly targeted workers, but also a broader range of economic actors by shifting their relevant outside options. Therefore, policies promoting work hour reductions should be considered carefully, as micro-data alone may provide an incomplete and potentially misleading picture of their overall impact.

2 Literature review

Several empirical studies examine recent instances of such reductions. In particular, two notable cases of legally mandated reductions in working hours, the French transition from a 39 to a 35 hour workweek (approved in 1998) and Portugal's shift from 44 to 40 hours in 1996, reveal the influence of institutional factors and policy design on outcomes.

When comparing France, Portugal, and Chile prior to the implementation of reduced working hours, certain distinctions emerge. Notably, the French and Portuguese cases differ significantly in pre-reform unemployment rates, 11.9% versus 7.6%, respectively. Chile, in comparison, faces an unemployment rate akin to that of Portugal but contends with a higher labor turnover, potentially impacting negatively on real wages for new jobs due to the weekly hours reduction.

Collective bargaining agreements, covering over 68% of employees in both France and Portugal, contrast sharply with Chile's less than 30% coverage. This discrepancy could amplify the negative impact of reduced working hours on real monthly wages in Chile due to lower collective bargaining capacity.

Furthermore, variations in part-time employment percentages (15% in France, 9% in Portugal, and 17.8% in Chile) and the proportion of service sector workers contribute to the nuanced economic landscapes. The higher proportion of part-time employees in Chile might impact the transition of workers from part-time to normal hours post-reduction. Additionally, the size of the service sector may influence (negatively) the feasibility of compensating for reduced hours through more intensive capital utilization.

The cases of Portugal in 1996, France in 1998-2002, and Chile in 2005 differ significantly, particularly in the crucial aspect of whether the hour reduction policy was implemented jointly with labor flexibility and/or financial incentives. Equally notable is the variance in the objectives pursued through these reforms.

France's reform aimed at reducing unemployment alongside a decrease in individual working hours. To achieve this, the reform introduced labor flexibility along with financial incentives. This would allow not to affect the labor cost per worker. Labor flexibility was introduced permitting firms to adjust the hours reduction on an annual basis, with an annual maximum of 1600 hours. So the working hours could be modified by the company according to its needs, provided that the working hours did not exceed 48 hours in one week, or an average of 44 hours per week over a twelve-week period. Meanwhile, the financial incentives consisted of subsidies to social security contributions with a huge fiscal cost.

Portugal's reform aimed directly at reducing individual working hours. Labor flexibility policies were also introduced, allowing adjustments on a four-month basis with a maximum of 50 hours per week.

The Chilean case in 2005, in contrast, was a quasi-natural experiment where the policy was implemented in isolation from other measures, such as labor flexibility or financial incentives.

Some empirical research has been conducted for the three mentioned cases. In the French case, Crepon et al. (2004), Jugnot (2002), Bunel (2004), and Gubian et al. (2004) find a positive effect on hours reduction and aggregate employment after the reform's implementation. OECD (2005) concludes that assessing the results of the workweek legislation is challenging, particularly due to the various confounding measures implemented.

Raposo and van Ours (2010) and Varejão (2004) find, for the Portuguese case, a positive effect on hours reduction. Varejão (2004) observe a reduction in the overall volume of work in the economy, but with a limited effect on aggregate employment. Conversely, Raposo and van Ours (2010) concludes that workers directly affected by the reform decrease their probability of losing their jobs.

Both the French and Portuguese cases underscore the influence of institutional factors and policy design. Presumably, the labor flexibility measures introduced in both instances allow for gains in productivity and a reduction in costs per worker.

For the Chilean case, Sánchez (2013) utilizes a difference-in-differences (DD) approach, focusing on employment transitions (job destruction), and concludes that there were no statistically significant effects due to the reform.

3 Institutional context

The labor market in Chile has undergone significant changes in the realm of legal working hours. In 2001, the Chilean Congress passed a bill that reduced the legal working hours, with implementation beginning in 2005. The legislation brought about a reduction from 48 to 45 weekly hours. Under this law, employers are mandated to compensate employees at a rate of 1.5 times overtime beyond the standard 45 hours, up to a maximum of 60 weekly hours. Furthermore, the distribution of these hours is constrained to 5 or 6 days a week, with a cap of 10 hours per day. However, certain occupational categories are exempt from these regulations, such as managers, individuals working without immediate supervision, athletes, drivers, and others.

In practice, this legal framework directly affects the formal sector of the economy, which is subject to government monitoring. Approximately 28% of employment in Chile falls under the informal sector, which underscores the limited reach of the legislation and its heterogeneous impact on specific segments of the labor market.

In recent years, starting in 2017, Chile witnessed a heightened political debate on a new reduction in legal hours worked from 45 to 40 hours per week, which had strong momentum in September 2019. Moreover, the proposal considered the lunch break as worked time, effectively reducing weekly hours to 35 hours. In Chile, hourly-wage jobs are rare, and a vast majority of formal jobs have monthly salary contracts. In consequence, the proposal also entailed a substantial increase in hourly wages, as any reduction in nominal monthly salaries was prohibited. While the Congress discussed this proposal, the "Social Unrest" movement of October 2019 took place. These large demonstrations, followed by violent protests, shifted the focus to broader societal issues, including constitutional changes. Despite this shift, public opinion remained supportive of the proposed reduction in working hours, as indicated by various polls.

Political debates on labor reforms in Chile have often lacked empirical evidence or quantitative models to assess their potential effects. Recognizing this gap, between September 2019 and January 2020, President Piñera commissioned the National Productivity Commission (CNP) to conduct an impact study. We took an empirical part on this study at that time, and some of the results we obtained in Villena-Roldán and Tejada (2020) are different from those obtained in this paper, mostly due to the different focus of the research question which leads to different definitions of treatment and control groups.

In June 2023, after a prolonged period of deliberation, Law 21561 was approved, solidifying the trajectory of legal working hours in Chile. This legislation outlines a gradual reduction in working hours, with the schedule set at 44 hours in 2024, 42 hours in 2026, and a final reduction to 40 hours in 2028. Notably, the law introduces a shift in measurement by considering a monthly average of weekly hours, offering flexibility to employers and employees in meeting the mandated hours without rigid adherence to weekly limits, qualitatively following similar reforms in Portugal and France. This marks a significant evolution in Chile's labor regulations, reflecting the culmination of extensive deliberations.

4 Data

4.1 *Encuesta de Protección Social* (EPS) (Social Protection Survey)

The EPS systematically tracks Chilean families and collects information on the labor market and the social protection system Bravo et al. (2008). Using the 2004 and 2006 survey waves, we constructed a balanced panel of labor histories for 18,807 individuals, with a monthly frequency covering the period January 2002–December 2005. Considering that the available time window spans the period between the announcement (December 2001) and the implementation of the workweek reduction (January 2005), we use the EPS to analyze the effect of the announcement and the potential anticipatory effect in preparation for the implementation of the new policy. The EPS reconstructs work histories from self-reported past work events including hours and wages. This survey also has information on individual characteristics such as age, gender and education level.

We complement the information available in the EPS with the Pension System's Pension History database (HPA) including active workers, pensioners, and deceased individuals. This database has, among other things, administrative information on the monthly taxable remunerations of the affiliates. The EPS-HPA pasting, within the period of analysis, generated a panel with a total of 10,659 individuals (56.7% of the total number of individuals observed in the EPS). It is important to note that individuals are observed in the HPA only if in the corresponding month they contributed to the social security system, that is, if they worked formally. Therefore, it is not possible to determine their activity outside this type of work. Moreover, the HPA data does not have information on the labor characteristics of the job, which is particularly important since we need hours worked to determine the treatment group. For this reason, we impute the values of labor characteristics observed in the EPS in the HPA observations only if the individual declares to be contributing to the social security. Although the reporting of formal work periods in the EPS may not coincide with those in the HPA, given the self-reported nature of the HPA, we were able to impute work characteristics to a total of 82.7% of the individual-month EPS observations (a number that corresponds to 8,140 individuals with some period of contribution).

4.2 *Encuesta Nacional de Empleo* (ENE) (National Employment Survey Rotating Panel)

The National Employment Survey (ENE) is the main source of information on the labor market in Chile. In particular, in this study we use its rotating panel structure. Each household included in an ENE sample is interviewed every three months, six consecutive times for urban households and twelve times for non-urban households. Once these interviews are completed, the household exits the sample. Month by month, groups of individuals enter and leave, so the composition of the people surveyed is never exactly the same. This limited longitudinal or panel structure (i.e., the same individuals are followed over a number of periods) will allow us to study the impact of the reduction in working hours on the same group of individuals. It should also be mentioned that this theoretical sequence of surveys is not recorded in many cases due to a lack of response on the part of the interviewees.

Although there is no single variable that identifies each person within the ENE database, it is possible to construct one that allows us to identify the same individual in several consecutive surveys using a set of variables, as described by García and Naudon (2012).

We also added other variables that help to specify this identifier. In addition, additional consistency criteria have been imposed on the individual histories, such as eliminating those in which the age of the person varies by more than two years in consecutive interviews. Finally, the data have been restricted to persons between 18 and 65 years of age.

5 Micro evidence

5.1 Empirical design

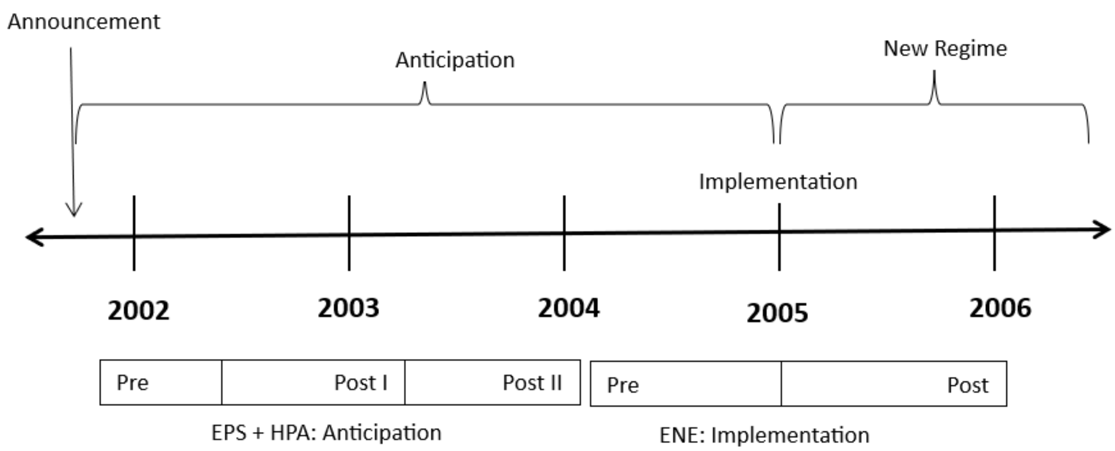
We use a difference-in-differences (DD) design to estimate the impact of the reform to reduce the legal working day from 48 to 45 hours, which came into effect in January 2005. This approach follows Crépon and Kramarz (2002), Chemin and Wasmer (2009) and Sánchez (2013) by assuming the existence of a group directly affected by the reform ("treated" in technical jargon) and a group that is not affected in principle ("control"). In particular, this assumes SUTVA, which implies no spillover effects in the sense that the outcomes of an individual, either in the treated or control groups, do not affect other individuals.

The timing of the events is summarized in Figure 1, which describes the sequence of events. The announcement and approval of the proposed reduction of hours were made in 2001, but the effective implementation was delayed until 2005 in order to facilitate the adaptation of the employers. We study an implementation effect comparing 2004 (pre-treatment) and 2005 (post-treatment) using ENE data. To assess the impact of the anticipation effect, we define the pre-treatment period in 2002, "early" anticipation in 2003, and late anticipation in 2004, and use EPS data.

We define treatment and control groups as similarly as possible using the ENE and EPS datasets. For both cases, we focus on private-sector salaried workers who were employed at least 75% of times they were interviewed in the year prior to the implementation, early or late anticipation dates, respectively. We also restrict both groups to having a sequence of responses in which the individual is employed in the last observation of the pre-treatment year. Since the treatment assignment should be, in theory, "as good as randomly assigned", we propose to make a comparison between groups with the most similar stance in the labor market. Both treated and control groups should exhibit a strong attachment to employment, but one group is directly affected while the other not. To draw a line between the treated and control groups, we do as follows:

- Control groups:

Figure 1: Timeline of events



- A: Employed for any range of hours +75% of responses in the year 2004 (ENE) or 2002 (EPS) and employed in last report in range 1-45 hours.
- B: Employed for any range of hours +75% of responses in the year 2004 (ENE) or 2002 (EPS) and employed in last report in range 40-45 hours.

- Treatment group: Employed for any range of hours +75% of responses in the year 2004 (ENE) or 2002 (EPS) and employed in last report in range 46-60 hours.

There is also another key identification assumption, which allows us to understand the estimates as a causal effect of the reduction in working hours on the group (or sub-population) under consideration: parallel trends. In our context, this means that controlling for observable factors, the outcomes of the treated and control groups would have varied the same in the absence of the reform (see for example Abadie, 2005). To make this assumption more likely to hold, we allow specific trends for the treatment and control groups. We can estimate the effect of interest by using the following equation:

$$Y_{is(i)t} = \alpha_i + \beta P_t + \gamma P_t D_{s(i)} + X_{it}\lambda + X_{it}D_{s(i)}\theta + \epsilon_{is(i)t} \tag{1}$$

where $Y_{is(i)t}$ corresponds to the outcome of interest (employment, wages, etc) of individual i, belonging to group $s(i)$ of some treatment or control; P_t is a binary variable that takes value 1 post-reform; $D_{s(i)}$ is a binary variable indicating whether individual i belongs to group $s(i)$, X_{it} is a set or vector of control variables that vary over time and across individuals and may include polynomial or flexible trends and variables capturing seasonality effects of employment or other factors.

The Average Treatment Effect on the Treated (ATET) is the expected impact of the policy on the directly affected group: those who worked 46 hours or more prior to the reform. This is the expected difference in changes in the outcome between affected and control groups, i.e.

$$\Delta_{ATET} = \gamma = \big(E[Y_{it}|P_t = 1, D_{s(i)} = 1, \alpha_i, X_{it}] - E[Y_{it}|P_t = 0, D_{s(i)} = 1, \alpha_i, X_{it}]\big) \\ - \big(E[Y_{it}|P_t = 1, D_{s(i)} = 0, \alpha_i, X_{it}] - E[Y_{it}|P_t = 0, D_{s(i)} = 0, \alpha_i, X_{it}]\big)$$

It is important to note that the estimated effects under the assumptions of parallel trends (or controlling for prior trends) allow us to estimate a causal impact with "internal validity" i.e., it effectively measures the causal impact of the reform on the treated group. However, with the assumptions expressed, it is not possible to extrapolate these results to other groups or subpopulations.

The impact described in equation (1) is estimated using fixed effects per worker using ordinary least squares with individual fixed effects. We also use the inverse probability weights reported by the survey.

We include as controls binary monthly seasonal variables due to the fact that there are occupations and economic sectors that vary their activity according to the months of the year, especially sectors such as agriculture, tourism and commerce.

Moreover, we include linear and quadratic trends for treatment and control groups, following the methodology proposed by Besley and Burgess (2004) and Angrist and Pischke (2009). This allows estimating causal effects by relaxing the assumption of parallel trends of the treatment and control groups, because the estimates are adjusted or controlled for (possibly nonlinear) prior trends that are specific to the treatment and control groups, allowing the impact of the reduction in working hours to be comparable in both groups.

As final consideration, we produce a set of results similar to the baseline results that are corrected for the problem of non-response or sample attrition to estimate the DD at the implementation. The rotating panel presents an important number of monthly surveys that were not conducted (or that could not be matched according to the criteria described in the appendix). In the constructed panel, those who are currently employed are more likely to return to the survey in the future, compared to their counterparts who are not employed (unemployed or inactive). This makes it more likely to observe employed individuals who become unemployed in the future than non-employed persons who become employed. Consequently, one may consider necessary to correct the estimates for this fact. In a panel data context, Wooldridge (2010) develops a flexible procedure for panel data, which in turn is an extension of the classical two-stage model of **?**. This essentially consists of estimating a selection equation, i.e., a probit model that predicts the probability of a survey taking place as a function of variables from the main model including treatment, policy introduction, demographic factors such as age, sex, educational level, and previous survey response behavior and employment status. These results can be found in the appendix. For the EPS-HPA there is no need to perform this procedure since the panel is strongly balanced, which means that there is no attrition due to the retrospective measurement of the labor stories.

As an inference consideration , we compute the standard errors of the DD model estimates assuming that the sampling error terms are potentially correlated at the individual level, e.g. standard errors are clustered at the individual level.

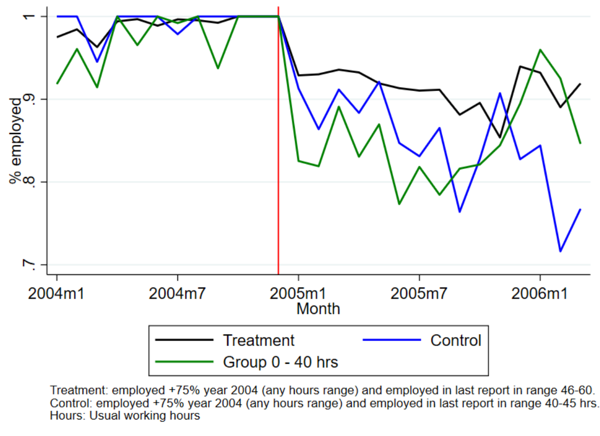
5.2 Describing outcomes for ENE (Implementation)

The Figure 3 depicts the proportions of the respective outcome variables within the treatment group, control group B (working 40-45 hours pre-treatment) and a group that encompasses people who worked less than 40 hours in the last reported quarter, i.e. individuals who are in the treatment group A (loose) but not in the group B (strict). The vertical red line marks December 2004.

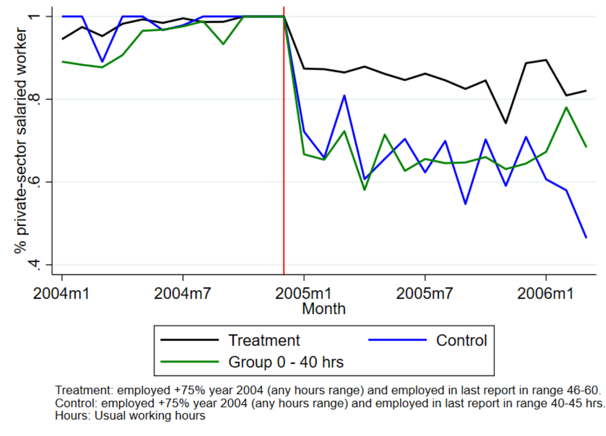
All graphs display data for treatment and control groups constructed based on usual working hours (as opposed to effective hours).

Subfigure 2a shows that the proportions of employed individuals are very close to 100% before the implementation of the reform. After that, there is a clear decline for all groups, especially for individuals working below 40 hours per week. In contrast, the treatment group, those working more than 46 weekly hours, exhibits the lowest decline after the implementation of the reform. In the subfigure 2b we observe that the aforementioned facts are exacerbated: a large decline in all groups working 45 weekly hours or less takes place, and the treatment group shows a smaller change. The comparison before and after the implementation of public employment is in subfigure 2c. There are very few individuals in that sector of the economy working before implementation by construction (remember that treated and control are defined as private salaried workers). However, after the reform was implemented, all groups substantially increased their proportion of public employment. While this effect is mechanical to some extent, since we defined the groups as private-sector salaried workers for most of 2004, it is notable that the control group shows a much more pronounced takeoff in comparison to the treatment group. For the self-employment proportion, depicted in sub-

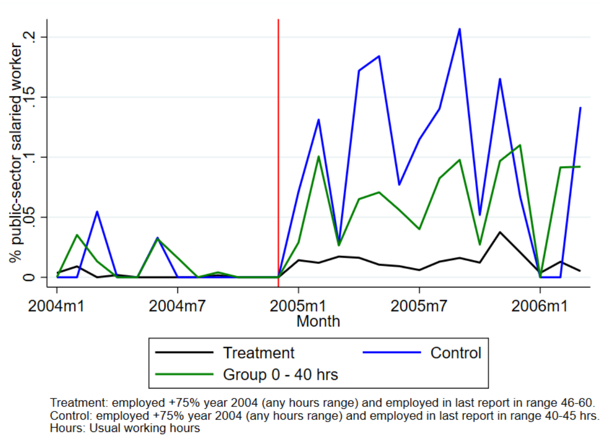
Figure 2: Outcomes evolution at the implementation of the legal hours worked reduction



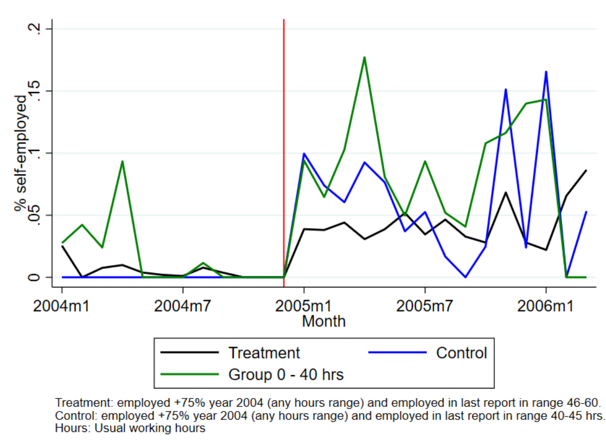
(a) Proportion of employed workers



(b) Proportion of private-sector salaried workers



(c) Proportion of public-sector salaried workers



(d) Proportion of self-employed workers

figure 2d, the treatment group shows a lower increase after the implementation, compared to the control B group, composed of salaried private individuals working in the range of 40 to 45 weekly hours.

In a nutshell, these figures show that all groups, not only those directly affected, change their trajectory after the implementation of the legal workweek reduction. While this is just descriptive data, it suggests that the impact of reforms may permeate other groups beyond the treatment, casting some doubt on the assumption behind the DD design.

5.3 Describing outcomes for EPS (Anticipation Effects)

The graphs depict the proportions of the respective variables within the treatment group, control group B, and a group that encompasses people who worked less than 40 hours in the last reported quarter. The vertical red line marks December 2002 and December 2003. Most series look quite similar in the pre-treatment phase (2002). In particular, Subfigures 3a and depict the trajectories of treatment and control B groups for the proportion of total employment and the proportion of private-salaried employed workers, respectively. Both series show that treatment drops clearly faster than the control B group does. While some outflows are expected from the treatment group over time, an ex ante comparable control B group (working 40-45 weekly hours) exhibits a noticeable steeper decline (same as for those employed less than 40 hours).

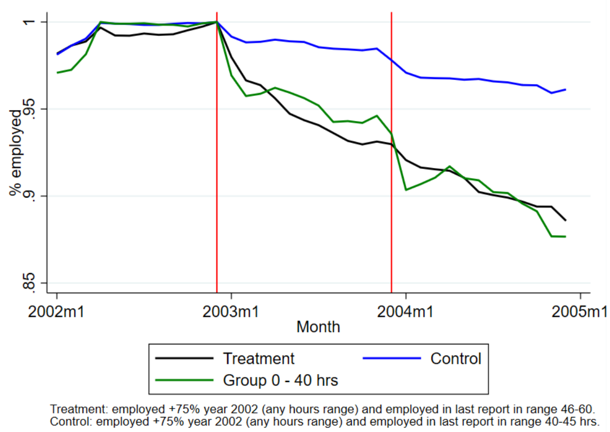
A different situation is observed at Subfigures 3c and 3d because after the anticipation dates 2003 and 2004 both treatment and control B groups evolve in a quite parallel fashion, suggesting that in the period 2001-2005 there was no clear anticipation effect in these variables.

5.4 Estimation results for micro data

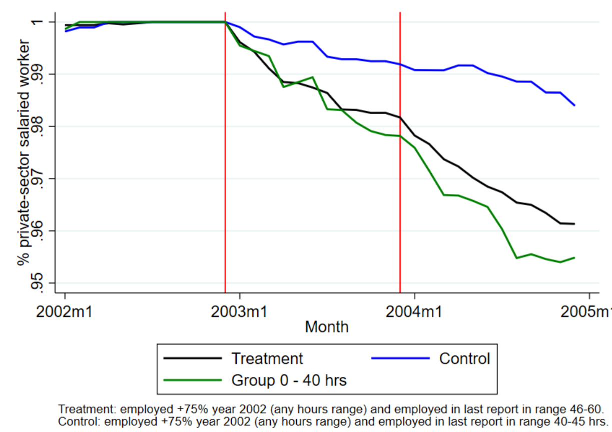
Table 1 shows the baseline DD estimation using usual (rather than effective) hours worked for the definition of both treatment and control groups. The table shows a negative but not-significant effect of the implementation in usual hours, with a point estimate ranging from -3.2 to -4.4 depending on the chosen control group. In both cases, a large majority of the workers are in the treatment group, which explains, to some degree, the large standard errors, clustered at the individual id level. The estimates for employment, salaried employment, and private-salaried employment in general yield non-significant positive point estimates for control group B, the most stringent. For public employment, we find a negative impact for control B , whereas for self-employment estimates become non-significant at conventional levels.

In Table 2, we re-estimate the models of Table 1 but excluding occupational ISCO groups 1 (high-level administrators and managers) and 2 (high-level professionals and scientists) to try to capture groups that are explicitly excluded from the scope of the legislation because they often work without direct supervision. In the column under the title “All sample” we show DD estimates and their standard errors when comparing the treated group and the control group B (40 to 45 hours workweek). Below the “Sample 1” title, we report the DD

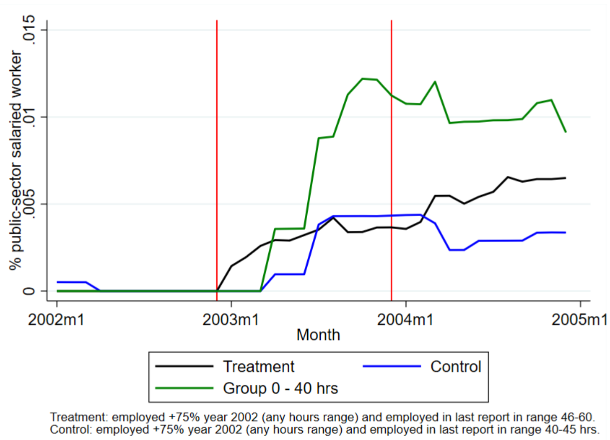
Figure 3: Outcomes evolution at anticipation dates of the legal hours worked reduction



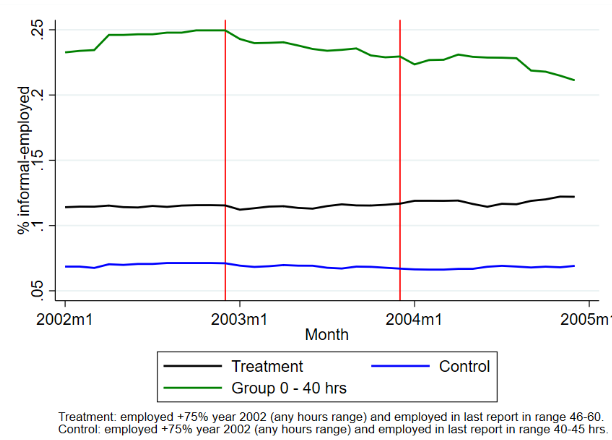
(a) Proportion of employed workers



(b) Proportion of private-sector salaried workers



(c) Proportion of public-sector salaried workers



(d) Proportion of self-employed workers

Table 1: ENE Diff-in-diff ATET estimation. Usual working hours.

	weekly hours		employed		salaried	
	Control A	Control B	Control A	Control B	Control A	Control B
Post JA05 $\times$ Tr 46-60	-4.487	-3.215	0.091	0.040	0.113*	-0.015
	(2.915)	(4.114)	(0.059)	(0.087)	(0.062)	(0.086)
R-Squared	0.109	0.118	0.053	0.048	0.086	0.079
Observations	20620	19504	20793	19672	20793	19672
Number of groups	5334	5042	5334	5042	5334	5042
Mean dep var	43.620	44.446	0.950	0.953	0.920	0.925
Prop treatment 46-60	0.892	0.944	0.892	0.944	0.892	0.944
	private-salaried		public-salaried		self-employed	
	Control A	Control B	Control A	Control B	Control A	Control B
Post JA05 $\times$ Tr 46-60	0.159**	0.078	-0.046	-0.093**	-0.064	0.012
	(0.064)	(0.092)	(0.041)	(0.044)	(0.048)	(0.056)
R-Squared	0.102	0.095	0.023	0.032	0.028	0.026
Observations	20793	19672	20793	19672	20793	19672
Number of groups	5334	5042	5334	5042	5334	5042
Mean dep var	0.909	0.914	0.011	0.011	0.026	0.024
Prop treatment 46-60	0.892	0.944	0.892	0.944	0.892	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours.

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

estimates excluding ISCO 1 and 2 groups. Results do not significantly change with respect to the Table 1. Even the negative impact on public employment vanishes once we exclude high-level occupations that are probably not affected by the reform.

Table 2: ENE Diff-in-diff ATET estimation. Comparison of Groups with and without Exclusion.

	weekly hours		employed		salaried	
	All sample	Sample 1	All sample	Sample 1	All sample	Sample 1
Post JA05 × Tr 46-60	-3.215	0.451	0.040	0.170*	-0.015	0.108
	(4.114)	(4.528)	(0.087)	(0.094)	(0.086)	(0.098)
R-Squared	0.118	0.123	0.048	0.054	0.079	0.087
Observations	19504	17899	19672	18053	19672	18053
Number of groups	5042	4793	5042	4795	5042	4795
Mean dep var	44.446	44.241	0.953	0.947	0.925	0.919
Prop treatment 46-60	0.944	0.956	0.944	0.956	0.944	0.956
	private-salaried		**public-salaried**		**self-employed**	
	All sample	Sample 1	All sample	Sample 1	All sample	Sample 1
Post JA05 × Tr 46-60	0.078	0.124	-0.093**	-0.016	0.012	0.014
	(0.092)	(0.102)	(0.044)	(0.036)	(0.056)	(0.062)
R-Squared	0.095	0.099	0.032	0.025	0.026	0.029
Observations	19672	18053	19672	18053	19672	18053
Number of groups	5042	4795	5042	4795	5042	4795
Mean dep var	0.914	0.912	0.011	0.007	0.024	0.025
Prop treatment 46-60	0.944	0.956	0.944	0.956	0.944	0.956

Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Hours: Usual working hours.

Sample 1: Non-Professional and Non-Managerial

Control: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

In Table 3 we re-estimate the models of Table 1. This time, we focus on the report of actual or effective hours worked, rather than usual. These estimates would make ENE and EPS more comparable because the latter only have actual hours. The point estimates seem attenuated with respect to those based on usual hours worked, as expected. This is due to the noisier measurement of actual hours, which are affected by sick leave days, parental leave, vacations, etc. Almost all results are non-significant at conventional levels.

Table 3: ENE Diff-in-diff ATET estimation. Actual working hours.

	weekly hours		employed		salaried	
	Control A	Control B	Control A	Control B	Control A	Control B
Post JA05 × Tr 46-60	-3.110	-1.271	0.015	0.018	0.025	0.002
	(2.148)	(2.528)	(0.043)	(0.052)	(0.047)	(0.056)
R-Squared	0.103	0.117	0.053	0.047	0.084	0.076
Observations	20612	18807	20799	18972	20799	18972
Number of groups	5337	4856	5337	4856	5337	4856
Mean dep var	43.615	44.557	0.950	0.955	0.920	0.927
Prop treatment 46-60	0.776	0.853	0.776	0.853	0.776	0.853
	private-salaried		public-salaried		self-employed	
	Control A	Control B	Control A	Control B	Control A	Control B
Post JA05 × Tr 46-60	0.061	0.053	-0.036	-0.052**	-0.038	-0.001
	(0.049)	(0.059)	(0.023)	(0.025)	(0.030)	(0.034)
R-Squared	0.097	0.089	0.018	0.022	0.027	0.026
Observations	20799	18972	20799	18972	20799	18972
Number of groups	5337	4856	5337	4856	5337	4856
Mean dep var	0.909	0.916	0.011	0.011	0.026	0.024
Prop treatment 46-60	0.776	0.853	0.776	0.853	0.776	0.853

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Actual working hours.

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

The anticipation effects are portrayed in Table 4. The interaction terms between years 2003 and 2004 and the treatment variable for individuals working between 46 and 60 weekly hours are interpreted as "early" and "late" anticipation effects using EPS data. In these cases, we do observe a significant negative impact on hours worked, a reduction of around 1.2 weekly hours on average among the tread population both in 2003 and 2004 for control group B in comparison to the treated group. According to the estimates, there is a significant negative effect in control group B of 2 percentage points in employment and 2.3 in salaried employment as an early anticipation effect. For late-anticipation effects, the impact seems somewhat weaker yet significant. The effect seems mostly driven by an adjustment of private salaried wages rather than public or self-employment.

To sum up, there is no significant evidence of micro-level effects on different kinds of employment at the reform implementation once we compare the directly treated to a control group that is ex ante comparable. Further refinements, such as excluding occupational groups likely unaffected by the reform, do not change the results. However, the evidence of the anticipation effect is more clear: there is some negative impact in employment, particularly salaried employment, over the transition period between 2001 and 2005.

This may be a result due to a combination of factors: first, the data size is limited so that we do not have power to tell apart small but non-zero effects. It's also true that the data spans over a short period to meaningfully assess the impact of such a reform. Moreover, the graphical analysis suggests that both groups exhibit changes during the anticipation period and after the implementation. Indeed, this is consistent with theoretical models of the labor markets under search frictions in which formal directly affected jobs play an important role in shaping the outside option of most if not all workers in the labor market. For this reason, in the next section we conduct an analysis at the aggregate level to overcome the limited time span of the data and the potential existence of general equilibrium effects or substantial spillovers.

6 Macro evidence

6.1 Aggregated impact using Local Projections

We analyze the dynamic effect of the 2005 legal hours reduction on different labor market outcomes at an aggregate level. This is done following the Local Projections approach, and using a synthetic panel at the levels of date-of-birth, sex, and schooling. This analysis complements the microeconomic perspective previously developed. Since the reduction in working hours is a policy that affects the entire labor market, it is highly likely that its effects will be observed at a general equilibrium level. Therefore, not only those directly affected by the policy will be treated. While micro-data can allow us to investigate the impact on these directly affected groups, it usually does not reflect the impact on groups that are not directly affected. The macroeconomic approach developed in this section aims to estimate the general impact of the reform on different labor market outcomes. It considers the joint

Table 4: EPS Diff-in-diff ATET estimation. Anticipation Effects.

	weekly hours		employed		salaried	
	Control A	Control B	Control A	Control B	Control A	Control B
Year 2003 × Tr 46-60	-1.166***	-1.176***	-0.010**	-0.020***	-0.013***	-0.023***
	(0.213)	(0.221)	(0.004)	(0.004)	(0.005)	(0.005)
Year 2004 × Tr 46-60	-1.573***	-1.254***	-0.001	-0.013**	-0.005	-0.019***
	(0.308)	(0.311)	(0.007)	(0.006)	(0.007)	(0.007)
R-Squared	0.045	0.052	0.038	0.039	0.052	0.053
Observations	215993	188259	215993	188259	215993	188259
Number of groups	6001	5230	6001	5230	6001	5230
Mean dep var	41.067	45.462	0.959	0.961	0.951	0.953
Prop treatment 46-60	0.533	0.620	0.533	0.620	0.533	0.620
	private-salaried		public-salaried		self-employed	
	Control A	Control B	Control A	Control B	Control A	Control B
Year 2003 × Tr 46-60	-0.003	-0.004*	0.000	0.001	0.003	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Year 2004 × Tr 46-60	-0.004	-0.007**	-0.000	0.001	0.004	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.005)	(0.005)
R-Squared	0.018	0.019	0.003	0.003	0.001	0.000
Observations	207119	180841	207119	180841	215993	188259
Number of groups	6001	5230	6001	5230	6001	5230
Mean dep var	0.989	0.989	0.003	0.002	0.122	0.098
Prop treatment 46-60	0.527	0.611	0.527	0.611	0.533	0.620

Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Control A: employed +75% year 2002 (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% year 2002 (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% year 2002 (any hours range) and employed in last report in range 46-60 hrs evolution of groups both directly and indirectly affected by the reduction in working hours, but without the possibility of distinguishing between these groups.

To estimate the dynamic impact of the reform at the labor market level, we adopt the Local Projections approach developed by Jordà (2005). This method, which has gained popularity in empirical macroeconomics, involves directly estimating in reduced form the response of outcome variables to a shock of interest (see Jordà, 2023, for a review of the different impact of shocks that have been studied in the literature using local projections). In our case, this shock is a change in hours worked. Specifically, we compare the labor market dynamics following a shock with those of a counterfactual scenario where the shock does not occur. Formally, assuming we observe panel data at the individual level with labor market outcomes, let's define a variable of interest for individual i at time t as $y_{i,t}$, a shock variable at time t as the change in working hours $h_{i,t}$ with respect to the hours worked prior to the reform $h_{i,0}$, and a set of control variables $\mathbf{x}_{i,t}$. Using this notation, Jordà (2005) proposes estimating a set of regressions for different future time horizons j in order to compute the response of $y_{i,t}$ to a shock of a given size, δ,

$$y_{i,t+j} - y_{i,t-1} = \Delta^j y_{i,t+j} = \alpha_i + \phi_t + \beta_j(h_{i,t} - h_{i,0}) + \mathbf{x}_{i,t}\gamma_j + \nu_{i,t+j}; \quad j = 0, 1, ..., J \qquad (2)$$

and then compute the accumulated impulse response at horizon j as the difference between two conditional forecasts:

$$\mathcal{R}_\Delta(j) = \mathrm{E}[\Delta^j y_{i,t+j} | h_{i,t} - h_{i,0} = \delta, \mathbf{x}_{i,t}] - \mathrm{E}[\Delta^j y_{i,t+j} | h_{i,t} - h_{i,0} = 0, \mathbf{x}_{i,t}] = \beta_j \delta \qquad (3)$$

where the first forecast represents the scenario in which the shock has occurred, and the second corresponds to a counterfactual scenario without the shock. In equation 2, α_i is the individual fixed effect, ϕ_t is the time effect, and $\nu_{i,t+j}$ is a moving average of the forecast errors from time t to time $t + j$.

Unfortunately, a panel with individual data with long time span is not available and therefore equation 2 cannot be estimated. As Deaton (1985) suggested, it is possible however to construct synthetic panel a cohort level to estimate a fixed effects model similar to equation 2 from repeated cross-sections (see Verbeek, 2008, for a survey of the literature on pseudo or synthetic panel data). The term "cohorts" is used by some authors to denote groups based on year of birth. In our context, however, we apply a wider definition of "cohorts" to encompass groups of individuals that possess shared characteristics, which typically include year of birth among others. Define a cohort c as an aggregation of i. Taking the average over c of equation 2 we can write the analogous of equation 2 at cohort level as:

$$\Delta^j \bar{y}_{c,t+j} = \bar{\alpha}_c + \phi_t + \beta_j(\bar{h}_{c,t} - \bar{h}_{c,0}) + \bar{\mathbf{x}}_{c,t}\gamma_j + \bar{\nu}_{c,t+h}; \quad j = 0, 1, ..., J \qquad (4)$$

where all the variables are defined as averages by cohort, that is $\bar{z}_{c,t} = (1/N_c)\sum_{i\in c} z_{i,t}$, and $\bar{\alpha}_c$ is the cohort fixed effect[2]. Using equation 4 we can compute the average accumulated impulse response at horizon j to a shock in working hours in period t of size $\bar{\delta}$ as:

$$\bar{\mathcal{R}}_{\Delta}(j) = \mathrm{E}[\Delta^j \bar{y}_{c,t+j} | \bar{h}_{c,t} - \bar{h}_{c,0} = \bar{\delta}, \bar{\mathbf{x}}_{c,t}] - \mathrm{E}[\Delta^j \bar{y}_{c,t+h} | \bar{h}_{c,t} - \bar{h}_{c,0} = 0, \bar{\mathbf{x}}_{c,t}] = \beta_j \bar{\delta} \tag{5}$$

The standard within estimator for equation 4 is equivalent to an instrumental variable estimator, where the cohort indicators are used as instruments, as noted by Moffitt (1993). Therefore, the selection of cohort groups must consider the assumptions of exogeneity and relevance, just as with any instrument.

We have pooled together data from the Chilean monthly National Employment Survey (ENE) for the time period of 2000 to 2008, and have defined the cohort c as comprising the following attributes: $c = \{sex, age, education\}$, each of them defined in the following manner:

- *sex*: we define the following groups, men and women.
- *age*: we define the following groups base on a 5 year window of the year of birth, $21-25$, $26-30$,..., $56-60$, and ≥ 60.
- *education*: we define the following groups, individuals who have complete primary education (8 years of schooling), secondary education (between 9 and 12 years of schooling) and tertiary education (more than 12 years of schooling).

With respect to the relevance of the cohort groups, all of these attributes, sex, age, and education, define the behavior of the labor market and therefore are important variables in explaining outcomes like employment, wages and hours worked. With respect to the exogeneity assumption, sex at birth and year of birth are clearly exogenous. The assumption that the level of schooling is exogenous is certainly not realistic. However, in this context, we do not directly use the years of schooling. Instead, we employ well-defined schooling groups, determined by exogenous thresholds relative to individual decisions (especially those related to a change in hours), in terms of the years of schooling required to transition from one group to another (see Blundell et al., 1998, for an example of the use of schooling groups in defining cohorts in synthetic panels). All in all the main specification to estimate the

[2] The individual effects within a cohort may change over time; however, we assume they remain constant. This assumption is reasonable if cohort averages are based on a large number of individual observations, as suggested by (Verbeek, 2008).

impulse response of a shock in hours worked is:

$$\Delta^j \bar{y}_{s,a,e,t+j} = \bar{\alpha}_s + \bar{\alpha}_a + \bar{\alpha}_e + \phi t + \beta^j (\bar{h}_{s,a,e,t} - \bar{h}_{s,a,e,0}) + \bar{\mathbf{x}}_{s,a,e,t}\gamma_j + \bar{\nu}_{s,a,e,t+j}; \quad j = 0, 1, ..., J \quad (6)$$

where t is a time trend and $\bar{\mathbf{x}}_{s,a,e,t}$ includes seasonal dummies, a pulse changes in the minimum wage (to isolate confounding effect related to the minimum wage policy), and lags of the outcome variable, that is $\bar{y}_{s,a,e,t-l}$ for $l = 1, ..., L$. The inclusion of these lags is justified for two reasons. Firstly, they allow for the capture of the internal propagation of the shock, as discussed in Jordà (2023). Secondly, they facilitate correct inference in light of the autocorrelated nature of the moving average structure of the error term, as noted in Plagborg-Møller and Wolf (2022).[3] It is worth mentioning that the equivalence between the within estimator and the IV estimator mentioned before still holds in the context of synthetic panels with dependent variable lags, although under stronger assumptions, as noted in Verbeek and Vella (2005).

The outcomes considered in $\bar{y}_{s,a,e,t}$ include the probability of being employed, the probability of being wage-employed (both total and distinguishing between private and public employment), the probability of becoming self-employed, the probability of being unemployed, the average duration of unemployment, and labor income.[4]

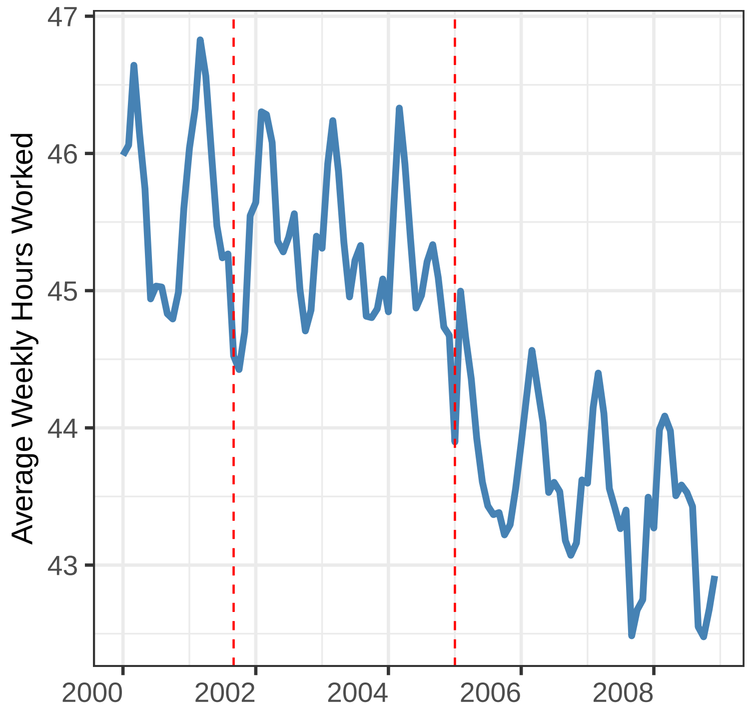
The hours worked, represented by the variable $h_{s,a,e,t}$, is an endogenous variable. Therefore, an instrument is necessary to identify the effect of the policy change (see Jordà and Taylor, 2016, for an example of the use of policy instrument in the local projection approach). To isolate the exogenous variation in hours due to the policy change, we use two dummy variables as instruments: (1) $d_t(announcement)$, which equals one from the moment the policy is announced (September 2001) and zero otherwise; and (2) $d_t(implementation)$, which equals one from the moment the policy is implemented (January 2005) and zero otherwise. Figure 4 shows the average weekly hours (usual) worked in the Chilean labor market by month from January 2000 to December 2008. The vertical lines represent the announcement and implementation dates. The average (usual) hours worked before the announcement was 45.7 hours per week. Following the announcement, the average hours worked decreased by an average of 24 minutes (-0.8%), indicating that the labor market began adjusting even before the implementation. After the implementation, the average hours worked dropped further, by approximately 2.1 hours on average (-4.7%) compared to the hours worked before

[3] We also employ Newey-West robust standard errors in the event of any remaining heteroskedasticity, given the existing heterogeneity across cohort groups.

[4] Questions about labor income are only included in the survey conducted each December. Therefore, the synthetic panel used to analyze this outcome can only be constructed with that annual frequency.

the announcement. Both changes are statistically significant, highlighting the relevance of the instruments. Additionally, from the perspective of the workers, both the announcement and the implementation dates can be considered exogenous.

Figure 4: Average Weekly Hours Worked



6.2 Results

Figure 5 presents the response functions of the probability of being employed in response to a unitary shock in hours, over a horizon of 36 months. These functions represent the estimated parameter $\hat{\beta}_j$ in equation 6 for each of the employment outcomes.

Panel (5a) shows that total employment tends to increase following the shock, and this effect is estimated with reasonable precision. The maximum accumulated effect is approximately 0.9 percentage points, reached at 2.5 years, implying that the probability of being employed increases by 1.9 percentage points in response to the average reduction of 2.1 hours. In turn, Panel (5b) shows that wage employment, which is directly affected by the policy, drops after the shock. After 2 years, the maximum unitary effect is around 0.8 percentage points, or 1.7 percentage points for an average reduction of 2.1 hours. This effect appears to be statistically significant. The probability of being employed as a waged employee in the private sector, as presented in panel 5c, decreases by around 0.5 percentage points (or 1 percentage point for an average reduction of 2.1 hours). This decrease occurs relatively quickly, within the first year after the shock. However, the precision of the estimator is much lower than in the previous cases. Considering the behavior of the total waged employment probability, it appears that the likelihood of being hired in the public sector also decreases, particularly after the second year of the shock.

If it is more likely for someone to become a worker, but less likely to be wage-employed, it must be true that the adjustment occurs in self-employment, which is included in total employment. Indeed, panel 5d shows the probability of working as self-employed, and we can observe that it increases by a maximum of approximately 0.65 percentage points following a unitary shock after two years, or by 1.4 percentage points for an average reduction of 2.1 hours. These results highlight the importance of the spillover effect from wage employment, which is directly affected by the reduction in hours, to other more flexible types of employment such as self-employment.

Figure 6 presents the response functions of other important labor market outcome, such as the probability of unemployment, the unemployment duration, the probability of no participation, and labor income, in response to a unitary shock in hours, over a horizon of 36 months.

Panel 6a shows that the probability increases marginally during the first two years (by less than 0.2 percentage points), but decreases sharply thereafter (reaching a maximum accumulated impact of approximately -0.5 percentage points). These estimates are quite precise and they are consistent with the behavior of total employment. The impact notorious on the duration of unemployment as is shown in Panel 6b. The duration of unemployment does not react initially; however, at the end of the first year following the shock, it increases sharply, up to 9%, which represents approximately three weeks (for a unitary shock). As employment increases, primarily driven by self-employment, the effect on unemployment duration starts to diminish after two years following the shock. These results are consistent with a labor market that becomes tighter for workers after the implementation of a policy that makes waged employment more costly. Again, these estimates are quite precise. Participation in the labor market decreases by a maximum of 0.5 percentage points (or 1 percentage point for an average reduction of 2.1 hours) as is shown in panel 6c. However, the estimates are not precise. Behind these results are probably those who, after searching for a more extended period of time in a tighter market, decided to leave the workforce. Again the spillover effects seems to be quite important.

Finally, panel 6d shows the impact on labor income. Since the synthetic panel is constructed only on an annual basis, there is a lower number of observations in the time dimension of the panel. This leads to estimated standard errors that are considerably higher. Nevertheless, the response of labor incomes is consistent with a tighter labor market where new hires have less bargaining power in setting wages. Also, due to the excess supply in more flexible types of jobs, labor income in those jobs should also fall. Indeed, labor income experiences a maximum drop of 3% two years after the shock (unitary).

7 Structural model

In this section, we construct a structural model to analyze the effects of the legal reduction of working hours in Chile in 2025 on the economy. Our goal is to make sense of the macroeconomic evidence obtained in the exercises using local projections. We could also provide a theoretical illustration of the reason why standard micro-level difference-in-difference approaches fail to capture policy-relevant effects.

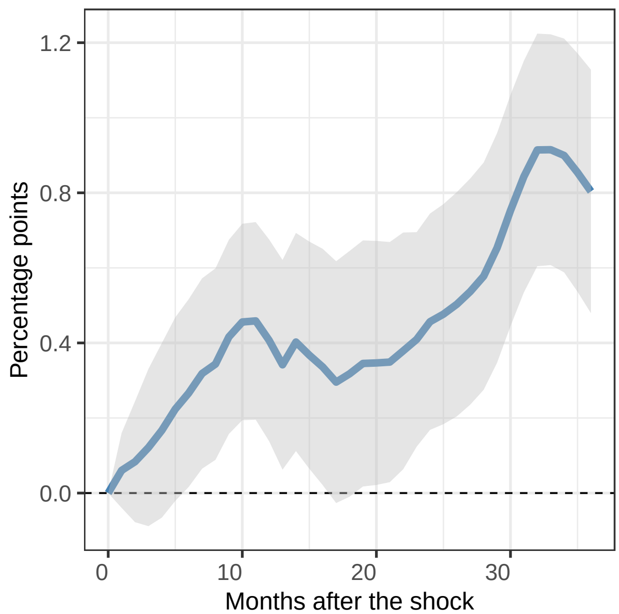
The model builds on the standard search and matching framework, incorporating features relevant to the Chilean labor market, such as a legally established maximum of hours worked, self-employment, and heterogeneity in worker skills and job productivity.

7.1 Key Assumptions and Environment

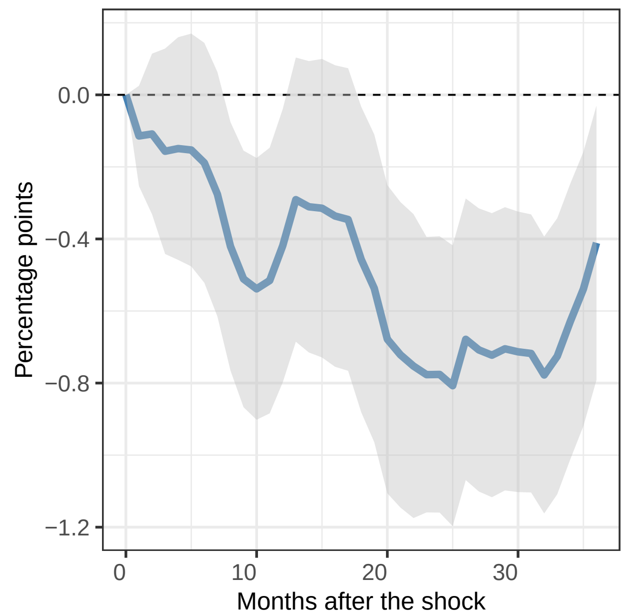
The model considers a continuous-time economy populated by a unit mass of agents. Agents operate in a labor market characterized by three states: unemployment u, informal self-employment s, and employment e. Both unemployment and self-employment are considered searching states where agents actively seek employment opportunities. The search process is assumed to be random. The matching function describes the technology available for job seekers in states u and s to meet formal employers in the economy, which post vacancies v, and form matches. We assume a constant returns-to-scale (CRS) matching function: $m(u+s,v)$. We define market tightness as $\theta = \frac{v}{u+s}$. Accordingly, we express the matching rate for firms as $\lambda(\theta) = \frac{m(u+s,v)}{v} = m\left(\frac{u+s}{v},1\right)$, and the job finding rate for workers as $\lambda(\theta)\theta = \frac{m(u+s,v)}{v}\frac{v}{u+s} = m\left(1,\frac{v}{u+s}\right)$

The model incorporates heterogeneity in the search effort, assuming that unemployed individuals exert higher search effort than self-employed individuals. Specifically, the effective job arrival rate for the unemployed is given by $\lambda^u(\theta) = \lambda(\theta)\theta$, while for the self-employed is $\lambda^s(\theta) = \delta\lambda(\theta)\theta$, where $\delta \in (0,1)$ captures the lower search intensity of the self-employed.

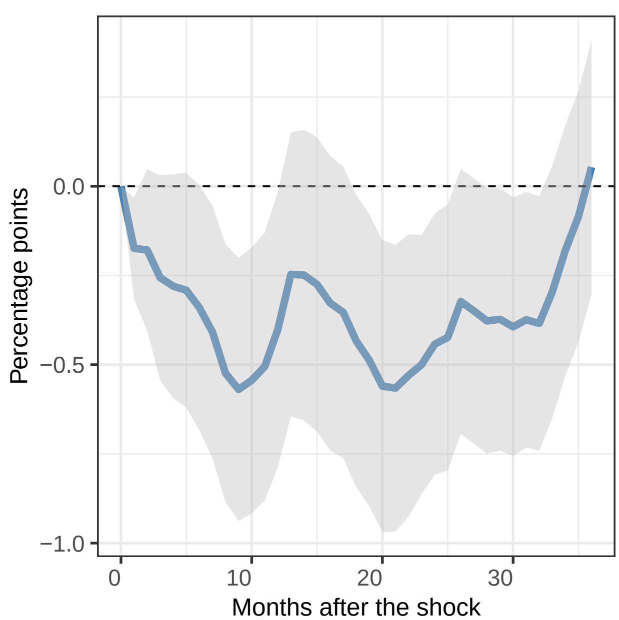
Figure 5: Response of Employment to a Shock in Hours



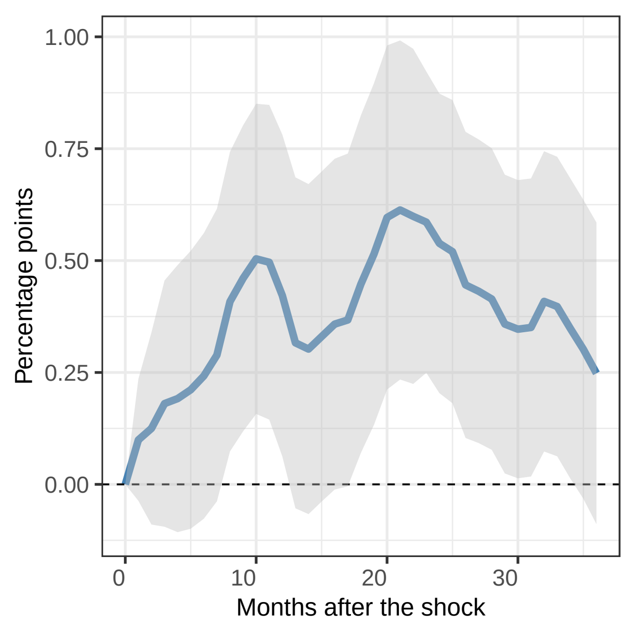
(a) Probability of Employment



(b) Probability of Waged Employment

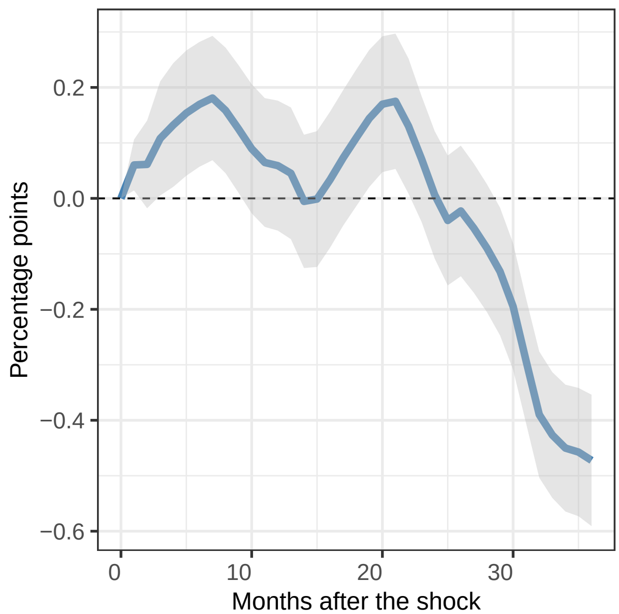


(c) Probability of Private Waged Employment

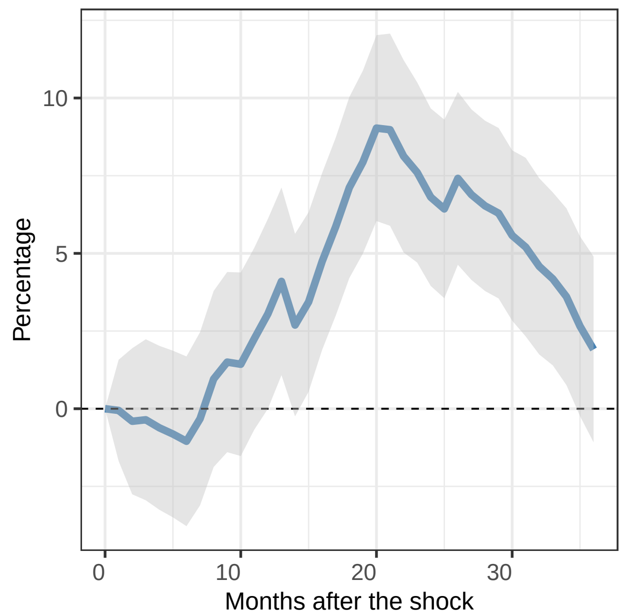


(d) Probability of Self-Employment

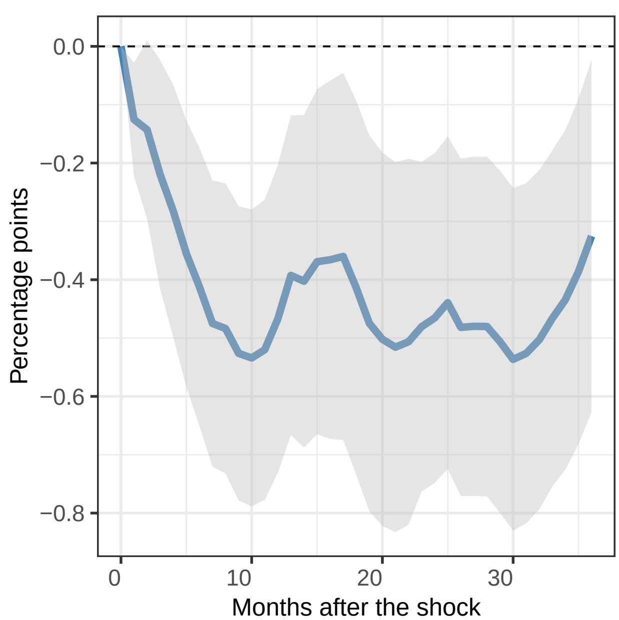
Figure 6: Response of Other Labor Market Outcomes to a Shock in Hours



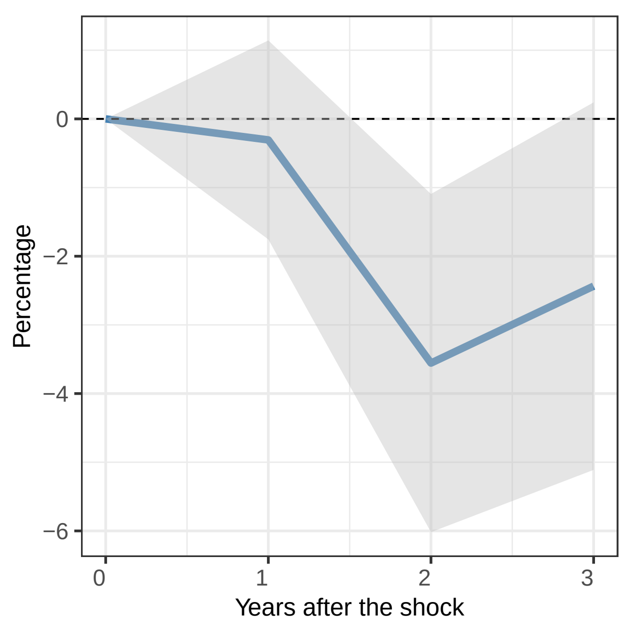
(a) Probability of Unemployment



(b) Unemployment Duration



(c) Probability of Inactivity



(d) Labor Income

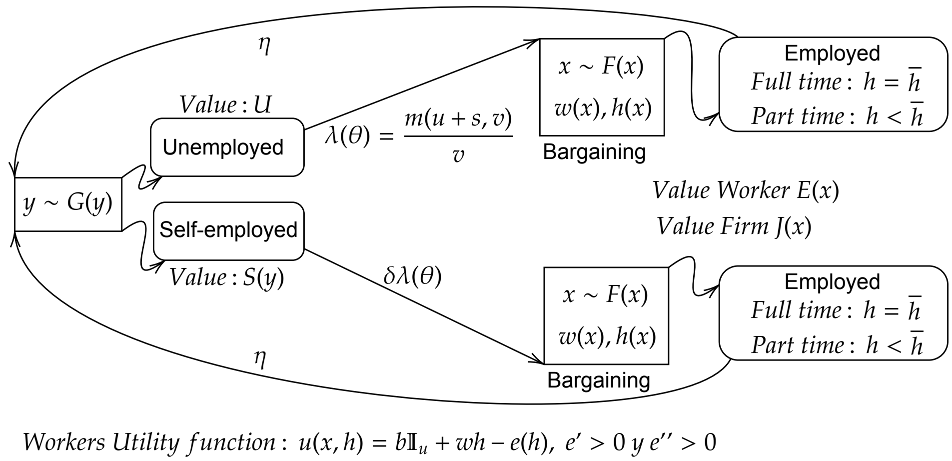


Figure 7: Diagram of the Economy

Unemployed individuals receive a flow utility b. The self-employed face idiosyncratic productivity shocks y drawn from a distribution $G(y)$. Upon successful matching, a worker-job match is formed with a match-specific productivity x drawn from a distribution $F(x)$ over the interval $[\underline{x}, \overline{x}]$. Employed workers face an exogenous termination rate η, while self-employed individuals face a termination shock ϕ.

Following Kudoh et al. (2019), the flow utility for an individual in state i working h hours is given by $u(x,h) = b\mathbb{I}_u + wh - e(h)$, where w is the wage, and $e(h)$ represents the disutility of working h hours, with $e'(h) > 0$ and $e''(h) > 0$. Hours are normalized between 0 and 1 without loss of generality. A common functional-form assumption is $e(h) = \frac{\epsilon h^{1+\nu}}{1+\nu}$.

Worker's problem

Based on the previous assumptions, the model's dynamics for workers can be conveniently characterized by a set of Bellman equations that describe the value associated with each labor market state. Let us define the lifetime values of unemployment, self-employment, and employment as U, $S(y)$, and $E(x)$, respectively.

The value function for the unemployed considers that an unemployed individual receives a flow utility b, receives job offers at poison rate $\lambda^u(\theta)$ and accepts a formal job only if the drawn of match-specific productivity x is such that $E(x) \geq U$. That is:

$$\rho U = b + \lambda^u(\theta) \int_{\underline{x}}^{\bar{x}} \max\{E(x), U\}\, dF(x) - \lambda^u(\theta) U$$

In turn, the value function for self-employed workers accounts for their current earnings

y, their optimal choice of working hours h_s, and their search for formal job opportunities, which arrive at a Poisson rate $\lambda^s(\theta)$. As before, the self-employed accepts a formal job only if the drawn of match-specific productivity x is such that $E(x) \geq S(y)$. The value function also accounts for the possibility of a destruction shock arriving at a Poisson rate ϕ, after which individuals must choose again between self-employment and unemployment, generating the value Q, which will be explained later. That is:

$$\rho S(y) = \max_{h_s} \left\{ yh_s - e(h_s) + \lambda^s(\theta) \int_{\underline{x}}^{\bar{x}} \max\{E(x), S(y)\} \, dF(x) \right.$$
$$\left. + \phi Q - [\lambda^s(\theta) + \phi] \, S(y) \right\}$$

The value of the employed depends on the draw of x, which influences the wage w and the hours h.

$$\rho E(x) = wh - e(h) + \eta Q - \eta E(x)$$

where Q represents the value of moving from self-employment or unemployment to employment in case of job loss.

Firm's Problem

Firms post vacancies at a flow cost κ. The value of a vacancy V and a filled job is given by

$$\rho V = -\kappa + \lambda(\theta) \int_{\underline{x}}^{\bar{x}} \max\{J(x), V\} \, dF(x) - \lambda(\theta) V$$

Conversely, the value of a filled job J as a function of the productivity x is

$$\rho J(x) = xh - wh + \eta V - \eta J(x)$$

7.2 Decisions

Self-employed individuals choose hours to maximize their utility. The first-order condition associated with this choice is

$$y - e'(h^s) = 0 \Rightarrow y = e'(h^s)$$

Assuming the effort function $e(h) = \frac{\epsilon h^{1+\nu}}{1+\nu}$, we obtain the following relationship between hours and income:

$$y = \epsilon h_s^{\nu} \rightarrow h_s = \left[\frac{y}{\epsilon}\right]^{\frac{1}{\nu}}$$

In turn, the self-employment entry or exit decision depends on a comparison between the value of unemployment and self-employment, which defines Q, the value obtained when a job ends, formal or self-employed.

$$Q = \int_{\underline{y}}^{\bar{y}} \max\{U, S(y)\}\, dG(y)$$

This defines a threshold productivity level y^* such that $S(y^*) = U$. The self-employment indicator function is therefore defined as $s(y) = \mathbb{I}(S(y) \geq U)$.

Wage Determination

Wages and hours are determined through Nash bargaining between workers and firms, considering the exogenous maximum legal hours $\bar{h}$ as a restriction.

$$\max_{w,h} (E(x) - Q)^{\beta} (J(x) - V)^{1-\beta}$$
$$s.to \quad h \leq \bar{h}$$

The resulting hourly wage is

$$w = \beta x + (1-\beta)\frac{[e(h) + \rho Q]}{h}$$

Using the slackness condition, the optimal hours and wage are given by:

$$h(x) = \begin{cases} \left[\frac{x}{\epsilon}\right]^{\frac{1}{\nu}} & x < \epsilon \bar{h}^{\nu} \\ \bar{h} & x \geq \epsilon \bar{h}^{\nu} \end{cases}$$
$$w(x) = \begin{cases} \left[\frac{1+\beta\nu}{1+\nu}\right] x + (1-\beta)\left[\frac{\epsilon}{x}\right]^{\frac{1}{\nu}} \rho Q & x < \epsilon \bar{h}^{\nu} \\ \beta x + (1-\beta)\left[\frac{\epsilon}{1+\nu}\bar{h}^{\nu} + \frac{\rho Q}{\bar{h}}\right] & x \geq \epsilon \bar{h}^{\nu} \end{cases}$$

A threshold productivity level x^* exists where a worker is indifferent between self-employment (working $(x/\epsilon)^{1/\nu}$ hours) and employment (working $\bar{h}$ hours).

Labor Market Equilibrium

The free entry condition for firms is:

$$\kappa = \lambda(\theta) \int_{\underline{x}}^{\bar{x}} \max \{J(x), 0\} \, dF(x)$$
$$\kappa / \int_{\underline{x}}^{\bar{x}} \max \left\{ \frac{h(x)\,(x - w(x))}{\rho + \eta}, 0 \right\} dF(x) = m\,(1/\theta, 1)$$

Combined with the Cobb-Douglas matching function $m(u+s, v) = (u+s)^{\gamma} v^{1-\gamma}$, this determines market tightness θ in equilibrium.

7.3 Steady State

In a steady state equilibrium, unemployment inflows and outflows need to equalize for a constant unemployment rate

$$\lambda(\theta)\theta\,[1 - F(x_u^*)]\,u = \eta G(y^*)e$$

Likewise, self-employment inflows and outflows are balanced to keep a constant mass of individuals in this state, integrating out all viable values of y

$$\int [\delta\lambda(\theta)\theta\,[1 - F(x_s^*(y))] + \phi]\, s(y) dG(y|y > y^*) = \eta\,[1 - G(y^*)]\,e$$

$$s = \int s(y) dG(y|y > y^*)$$

We finally normalize the size of the population to 1 so that the following condition holds

$$u + s + e = 1$$

7.4 Model results

Estimation Method and Identification

To estimate the model parameters, we use data from the 2009 CASEN survey. Specifically, we use the distributions of labor market states —unemployment, self-employment, part-time employment, and full-time employment (working the legal hours). Additionally, we use unemployment (ongoing) duration for unemployed individuals; hourly wages, hours worked, and ongoing job duration for the employed; and finally, hourly earnings, hours worked, and ongoing duration for the self-employed. We use the 2009 survey instead of those from around the 2005 reform (2003 or 2006) due to data limitations in earlier versions of the survey, most notably the lack of duration information. The goal, therefore, is to estimate and characterize the economy after the 2005 reform and then use counterfactual experiments to roll back to the 2004 labor market conditions before the reform. We analyze skilled and unskilled workers separately, defining skilled workers as those with tertiary education and unskilled workers as those with less than tertiary education.

We estimate the model's primitive parameters using the Method of Simulated Moments (MSM). Let Θ denote the set of parameters to be estimated, M_N^D the set of appropriately chosen statistics derived from our data sample of size N, and $M_T(\Xi)$ the corresponding set of simulated statistics obtained from a sample of size T generated under the steady-state equilibrium implied by Θ. Then, our MSM estimator $\hat{\Theta}$ satisfies:

$$\hat{\Theta}_{N,T}(W) = \text{argmin}_{\Theta} \left[M_N^D - M_T(\Theta)\right]' W_N \left[M_N^D - M_T(\Theta)\right] \tag{7}$$

where W is a symmetric, positive-definite weighting matrix. To construct this matrix, we use the inverse of the bootstrapped variance of each moment in the sample as the elements of its diagonal. The bootstrapped variance, in turn, is computed by drawing random samples with replacement from the 2009 CASEN survey original sample and estimating the moments for each draw. Finally, to construct the standard errors of the estimated parameters based on the bootstrapped moments, we proceed in a similar fashion. Specifically, for the moments computed from each random sample in the bootstrap, we solve equation (7) a number of times (replications) and then compute the standard errors of all of those estimated parameters.

Our identification strategy relies on the standard arguments of Flinn and Heckman (1982).

First, the productivity distribution in self-employment is directly identified from the hourly earnings data for this labor market state. The observed distribution is a truncated version of the reservation earnings for the self-employed. Therefore, the original earnings distribution (i.e., the productivity distribution) can be recovered by inverting the observed distribution. According to Flinn and Heckman (1982), this is possible if the underlying distribution belongs to a location-scale family. We assume that $G(y)$ follows a lognormal distribution with parameters μ_y and σ_y, which satisfy the *recoverability condition*. Additionally, since the (log) location and scale parameters fully characterize the distribution, we use the mean and standard deviation of observed hourly earnings as key moments to identify μ_y and σ_y.

Second, the parameters ν and ϵ are identified from the relationship between hourly earnings and hours worked in self-employment. From the optimal hours worked in this state, we have $\nu \log h_s = \log y - \log \epsilon$. By computing the expectation and variance of this expression and then applying the delta method to approximate the relationship between the expectations and variances of y and h_s, we obtain $\nu \approx \left(\frac{E[h_s]}{E[y]}\right)\sqrt{\frac{V[y]}{V[h_s]}}$ and $\epsilon \approx \exp\left(\log E[y] - \nu \log E[h_s]\right)$.[5] These last two expressions show that the relationship between the mean and variance of earnings and hours worked contains information about these parameters. As key additional moments, we use the mean and standard deviation of weekly hours worked in self-employment.

Third, the productivity distribution in employment is identified from hourly wage data. As before, observed wages correspond to accepted wages. Therefore, to recover the underlying productivity distribution $F(x)$, it is first necessary to map wages into productivity and then invert the truncated distribution. The mapping is done using the wage equation, and the *recoverability condition* is ensured, as before, by assuming that F(x) follows a lognormal distribution with parameters μ_x and σ_y. As key additional moments, we use the mean and standard deviation of hourly wages in employment. Moreover, given that the wage equation in this model heavily depends on hours and is highly nonlinear, we also include the mean and standard deviation of weekly hours worked in employment as moments. We also include the 5th percentile at the bottom of the wage distribution as a moment to provide information on reservation values, which are directly related to the value of the outside option ρQ.

Fourth, information on the (ongoing) duration in each labor market state and the distribution of labor market states is key to identifying the model's dynamics, which are governed by the arrival rates λ^u, λ^s, ϕ, and η. Given that we assume a steady-state equilibrium, all inflows and outflows from each labor market state must cancel out. Additionally, since the arrival rates are constant (i.e., they do not exhibit duration dependence), the duration data provides direct information into the constant hazard rates, while the steady-state condition imposes restrictions on the determination of the rates u, s, and e. We include the mean and standard deviation of duration (in months) in unemployment, self-employment, and employment as key additional moments. It is important to also note that upon termination, there are multiple exit options—unemployment or self-employment. Therefore, we also include as a moment the proportion of currently unemployed individuals who were previously self-employed.

Finally, note that even though λ^u and λ^s are endogenous variables, they can be treated as parameters on the supply side of the model because they serve as the only link between the demand and supply sides. According to the discussion above, these rates are identified,

[5] Recall that the delta method uses the first order Tayor approximation: $\log(y) \approx \log(E[y]) + \frac{(y-E[y])}{E[y]}$, which implies that the mean and variance can be approximated by $E[\log(y)] \approx \log(E[y])$ and $V[\log(y)] \approx E[y]^{-2}\mathrm{V}[y]$

and therefore, we then use them, along with parametric assumptions, to recover the parameters of the demand side. In particular, knowledge of the matching function allows us to recover the cost of posting vacancies κ and the search effort of the self-employed δ using the firm's equilibrium condition under free entry ($V = 0$). Additionally, the flow utility of unemployment, b, can be recovered from the Bellman equation for the unemployed.

The parameters that cannot be identified from the available data are those related to the bargaining parameter, the matching function, and the discount rate. For the bargaining parameter, we set $\beta = 0.5$, assuming equal bargaining power between workers and firms. For the matching function, we assume a Cobb-Douglas specification with elasticity $\gamma = 0.5$. The last assumption follows the Hosios condition directly (Hosios, 1990). Finally, we set $\rho = 0.1$, following Moore et al. (2020) for the case of Chile.

For the institutional parameters, we set the maximum legal hours to $\bar{h} = 0.56$, which corresponds to 45 hours when total hours are normalized to 80. Given the identification strategy described above, the set of parameters to be estimated are:

$$\Theta = \{\delta, \eta, \phi, b, \mu_x, \sigma_x, \mu_y, \sigma_y, \kappa, \epsilon, \nu\}$$

Estimation Results

Table 5 presents the estimated parameters of the model.

Given the matching function (γ) and the free-entry condition, the estimated cost of posting vacancies, κ, implies a labor market tightness of 4.7 (30) and an arrival rate of job offers while unemployed λ^u of 0.18 (0.45) for skilled (unskilled) workers. These arrival rates indicate that, on average, job offers arrive every 5 months for skilled workers and every 2 months for unskilled workers. It is also worth mentioning that for firms, it is more costly to maintain an open vacancy when looking for a skilled worker than for an unskilled one.

Using the estimated parameter δ, which reflects the gap in job search intensity between the self-employed and the unemployed, the arrival rate of job offers while unemployed, λ^s, is practically zero for both skilled and unskilled workers. This result reflects the fact that the duration of self-employment is particularly long, especially for unskilled workers, suggesting that transitions out of self-employment are rare. Our interpretation is that self-employment is not merely a substitute for unemployment during the job search process but rather an activity that workers actively choose to remain in.[6]

[6]It is important to note that even though the duration of self-employment is long, we do not know from the data what types of activities these workers engage in. They could have transitioned between different self-employment activities over time.

The estimated termination rates while employed (η) indicate that jobs last, on average, 8 years for skilled workers and 6 years for unskilled workers. While self-employed, the estimated arrival rate of income shocks (ϕ) implies that they occur, on average, every 10 years for skilled workers and every 14 years for unskilled workers.

The estimated parameters for the match-specific productivity distribution for employees, μ_x and σ_x, imply that for skilled workers, the unconditional average productivity is 7.5 US dollars per hour, with a standard deviation of 6.8 US dollars per hour. As expected, these figures are much lower for unskilled workers. In particular, their unconditional average productivity is 1.8 US dollars per hour, with a standard deviation of 4.8 US dollars per hour.[7] For the self-employed, the estimated parameters for self-employment income opportunities, μ_y and σ_y, imply that the unconditional average productivity and its standard deviation are both 1 US dollar per hour for skilled workers. For unskilled workers, the unconditional average productivity is 0.4 US dollars per hour, with a standard deviation of 0.3 US dollars per hour.

Finally, the estimated parameters of the utility cost function of dedicating hours to the labor market, ϵ and ν, imply that for a skilled worker working the legal hours, the utility cost is 0.7 US dollars per hour, while for an unskilled worker, it is 0.1 US dollars per hour (7 times lower).

Table 6 presents the model's fit across several dimensions for both skilled and unskilled workers. Three points are worth highlighting. First, the model generally provides a good fit for the distributions across labor market states for both worker types. Where the model performs relatively poorly, particularly for skilled workers, is in capturing transitions from self-employment to unemployment. Second, regarding self-employment earnings, the model captures the mean relatively well. However, it underestimates the dispersion of the distribution, particularly for unskilled workers. A similar pattern is observed for wages in employment: while the model fits the mean reasonably well, it falls short in capturing the dispersion for skilled workers. In contrast, for unskilled workers, the model performs relatively well. Finally, with respect to the distributions of hours worked, the model provides a good fit for both types of employment—self-employment and wage employment—as well as for both skilled and unskilled workers. Similarly, the model provides a very good fit for the distribution of duration across the board.

[7] Recall that if x is log-normal distribution with parameters μ and σ, then $E[x] = \exp\left(\ \mu + \frac{\sigma^2}{2}\ \right)$ and $V[x] = \left[\ \exp(\sigma^2) - 1\ \right]\ \exp\left(2\ \mu + \sigma^2\right)$.

Table 5: Estimated Parameters

Parameter	Skilled		Unskilled	
	Estimate	Std.Err.	Estimate	Std.Err.
δ	0.0001	0.0002	0.0006	0.2473
η	0.1287	0.0071	0.1513	0.0149
ϕ	0.1052	0.0113	0.0735	0.0187
b	-2.921	0.3378	-0.3239	0.0551
μ_x	1.7200	0.0826	-0.4824	0.1647
σ_x	0.7778	0.1120	1.4534	0.1070
μ_y	-0.4466	0.1167	-1.0207	0.1435
σ_y	0.8335	0.0779	0.6389	0.0752
κ	2.0480	0.2430	0.1660	0.0546
ϵ	13.923	3.7898	13.2203	15.6795
ν	2.1774	0.4093	4.4617	0.7203
Loss	6864.0		6226.0	

NOTE: Bootstrapped standard errors. The fixed parameters in estimation are: the matching elasticity $\gamma = 0.5$; the bargaining power $\beta = 0.5$; discount rate $\rho = 0.1$; and the maximum legal hours $\bar{h} = 0.56$ (with a normalization of 80 hours).

Table 6: Moments Fit

Statistic	Skilled			Unskilled		
	Model	Data	Weight	Model	Data	Weight
u	0.05	0.06	74814.0	0.05	0.06	932539.0
s	0.15	0.12	38679.0	0.18	0.17	72682.0
e	0.80	0.82	26315.0	0.77	0.77	56976.0
$Pr[h = h_{max}\|e]$	0.65	0.69	16500.0	0.80	0.85	59146.0
$Pr[s \rightarrow u\|u]$	0.12	0.05	28146.0	0.11	0.07	8250.0
$E[w\|s]$	2.64	3.29	300.0	1.12	1.61	953.0
$SD[w\|s]$	1.31	2.91	246.0	0.38	1.33	193.0
$P5[w\|s]$	1.64	0.62	226.0	0.81	0.40	4309.0
$E[w\|e]$	3.93	4.38	354.0	1.75	1.84	4934.0
$SD[w\|e]$	1.61	3.11	424.0	1.17	1.25	9906.0
$P5[w\|e]$	1.80	1.08	1762.0	0.81	0.73	7199.0
$E[h\|s]$	0.46	0.55	9112.0	0.57	0.56	28926.0
$SD[h\|s]$	0.09	0.23	157042.0	0.04	0.24	86267.0
$E[h\|e]$	0.53	0.53	594119.0	0.56	0.55	2740979.0
$SD[h\|e]$	0.06	0.08	170710.0	0.01	0.05	374932.0
$E[t\|u]$	0.39	0.70	973.0	0.34	0.41	4645.0
$SD[t\|u]$	0.44	1.14	28.0	0.38	0.81	65.0
$E[t\|s]$	8.87	8.18	43.0	10.89	10.30	93.0
$SD[t\|s]$	7.81	7.75	12.0	8.65	9.61	35.0
$E[t\|e]$	7.47	6.72	62.0	6.56	6.09	144.0
$SD[t\|e]$	6.95	7.41	64.0	6.36	7.35	138.0

7.5 Counterfactual experiments

We use our model of the Chilean economy as portrayed by the CASEN 2009 survey (similar to the American Community Survey), four years after the implementation of the workweek reduction. We consider this a reasonable time after the policy change so that the key variables have reached their steady-state values. In addition to this assumption, we consider that the estimated parameters are "deep" in the sense that they are invariant to the implementation of the policy. In other words, they are immune to the Lucas (1976) critique.

Once we fit the model under a 45-hour workweek regulation in 2009, we can simulate counterfactual scenarios for skilled and unskilled workers under a 48-hour workweek before 2005 or a 40-hour workweek after 2028 (assuming away transition to new steady states) in Table 7. In line with the macro evidence obtained from local projections, self-employment was substantially lower under a longer 48-hour workweek (11% and 13% for unskilled and skilled workers, respectively). In contrast, we obtain very limited impact of the workweek regulation change in the unemployment rate. Due to the hours reductions, total employment exhibits a moderate increase in employment for both unskilled and skilled groups. These results are clearly aligned with the macro empirical evidence from local projections.

The reform also generated a decline in market-tightness, especially for the unskilled group. A similar impact occurs in the arrival rate of jobs for the unemployed. The effect of the arrival rate for the self-employed is essentially negligible regardless of the prevailing workweek regulation. These results closely align with the impact effects obtained in the local projections exercise. To inspect the key mechanisms, we focus on the impact of policy changes on the cutoffs that define endogenous labor market transitions in the model.

The threshold value defining the waged-job market productivity $\bar{x}$ declines by 15% and 33% after the reform for skilled and unskilled workers, respectively, making it much more likely for workers to become self-employed. The cutoff $\bar{x}_u$ that indicates the threshold of market productivity that makes a worker indifferent between unemployment and self-employment also declines by 10% and 7% for skilled and unskilled workers, respectively. These changes explain that a sizable share of workers choose to become self-employed rather than keep searching for jobs that are less likely to be obtained and pay lower wages. Finally, the threshold of self-employment productivity $\bar{y}$ also declines, mostly due to the reduction of wages in the formal sector.

Productivity and wages also fall by 4% and 2-3%, respectively, due to the workweek reduction. This is a direct consequence of lower hours worked in spite of a reduction in cutoff values, indicating that less productive workers who used to work in the formal, regulated sector now become self-employed. Productivity inequality tends to increase for skilled workers, but wages do not. The inequality effects for unskilled workers are small.

In terms of hours worked, the reform effectively achieves its goal: for skilled workers, hours decline by 2% and 5% for self-employment and formal employment, respectively.

We also use the model to foresee the potential impact of the already approved law mandating a workweek reduction to a 40-hour workweek in 2028. It's important to consider that the model is highly stylized and does not take into account many realistic aspects such as an intensive margin of hours, compositional changes, inactivity transitions in the labor market, etc. Moreover, the regulation also considers a monthly average of 40 hours per week, rather than the fixed 45 hours that were enacted by the old regulation. This additional margin of flexibility may help employers to organize their productive activities in a more efficient way, partially offsetting the results derived from a lower equilibrium productivity.

Having said these warnings, our exercise foresees an increase of around 30% of self-employment for both skilled and unskilled workers under a 40-hour regime, whereas formal employment is expected to drop by nearly 6%. Since unemployment is the most effective way to achieve a formal job, this variable is also expected to decline mostly due to the lower attractiveness of formal employment. Market-tightness declines by 8% for skilled workers and 15% for unskilled ones, and the arrival rate decreases by 4% and 8% for skilled and unskilled workers, respectively. Therefore, unemployment durations are likely to increase according to the model.

In line with the other facts, all cutoffs in the model sizably decline, indicating that self-employment becomes an easier and more preferred choice in the labor market. We expect hourly wages to drop by 5% and 7% for skilled and unskilled jobs in the formal sector. The average wages for self-employment also decline, mostly due to the negative selection of workers coming from employment and unemployment. Inequality, on the other hand, declines. Hours worked, as expected, decline by 9%-10% in formal jobs and 6%-2% for skilled and unskilled self-employed, respectively.

7.6 A primer on spillover effects in a DD framework

We relate micro DD and structural model.We consider an observed outcome variable $y = \{s, e, u, w\}$. The treated group emcompasses people working before the policy change with regulated hours $\overline{h}_0$ and aggregate conditions A_0, which considers spillovers on other "untreated" groups

$$T(x) = \mathbb{I}[x > x^*(\overline{h}_0, A_0)]$$

Table 7: Policy Experiments

Statistic	Skilled					Unskilled				
	45 hours	48 hours		40 hours		45 hours	48 hours		40 hours	
	Value	Value	Ratio	Value	Ratio	Value	Value	Ratio	Value	Ratio
Labor Market States										
u	0.05	0.05	1.01	0.05	0.93	0.05	0.05	0.99	0.04	0.93
s	0.15	0.13	0.87	0.2	1.32	0.18	0.16	0.89	0.23	1.3
e	0.8	0.82	1.02	0.75	0.94	0.77	0.79	1.03	0.72	0.94
$Pr[\bar{h}\|e]$	0.65	0.57	0.88	0.76	1.17	0.8	0.65	0.82	1.0	1.25
Arrival Rate of Jobs and Market Tightness										
θ	4.73	4.91	1.04	4.34	0.92	29.89	32.31	1.08	25.29	0.85
λ_u	2.17	2.22	1.02	2.08	0.96	5.47	5.68	1.04	5.03	0.92
λ_s	0.0	0.0	1.02	0.0	0.96	0.0	0.0	1.04	0.0	0.92
Cutoff Productivities										
$\tilde{x}$	3.98	4.58	1.15	3.08	0.77	1.01	1.35	1.33	0.6	0.59
$\tilde{x}_u$	1.37	1.52	1.1	1.05	0.76	0.72	0.77	1.07	0.62	0.86
$\tilde{y}$	1.6	1.72	1.07	1.35	0.85	0.79	0.83	1.05	0.71	0.9
Wages/Earnings (Thousands per hour)										
$E[y\|s]$	2.64	2.75	1.04	2.33	0.88	1.12	1.17	1.04	1.03	0.92
$SD[y\|s]$	1.31	1.25	0.96	1.19	0.91	0.38	0.38	1.01	0.36	0.96
$E[w\|e]$	3.93	4.02	1.02	3.73	0.95	1.75	1.8	1.03	1.62	0.93
$SD[w\|e]$	1.61	1.61	1.0	1.6	1.0	1.17	1.19	1.01	1.16	0.99
Hours ($\times 80$)										
$E[h\|s]$	0.46	0.47	1.02	0.43	0.94	0.57	0.58	1.01	0.56	0.98
$SD[h\|s]$	0.09	0.08	0.95	0.09	0.98	0.04	0.04	0.99	0.04	1.02
$E[h\|e]$	0.53	0.56	1.05	0.48	0.91	0.56	0.59	1.05	0.5	0.9
$SD[h\|e]$	0.06	0.07	1.19	0.04	0.73	0.01	0.02	2.12	0.0	0.0

NOTE: Results are based on simulations of 10.000 individuals. The column Ratio presents the ratio with respect to the benchmark (45 hours).

Using the potential outcomes notation for treated (T) and untreated (U), we can write the observed outcome as

$$y_G(x) = y_G^1 T(x) + y_G^0(1 - T(x))$$

for $G = \{T, U\}$, where the superscript on y_G^s denotes the outcome occurring under treatment $s \in \{0, 1\}$ (1 denoting treatment and 0 no treatment).

The Average Treatment Effect on the Treated, assuming no spillovers, is

$$ATET_0 = E[y_T^1|\overline{h}_1, A_0] - E[y_T^0|\overline{h}_1, A_0]$$

The standard DD estimator compares the effect of policies under different realized aggregate conditions (depending on treatment)

$$DD = (E[y_T|\overline{h}_1, A_1] - E[y_T|\overline{h}_0, A_0]) - (E[y_U|\overline{h}_1, A_1] - E[y_U|\overline{h}_0, A_0])$$

This can be decomposed

$$\begin{aligned} DD =& (\underbrace{E[y_T^1|\overline{h}_1, A_1] - E[y_T^1|\overline{h}_1, A_0]}_{\text{spillover on treated}}) + (\underbrace{E[y_T^1|\overline{h}_1, A_0] - E[y_T^0|\overline{h}_0, A_0]}_{\text{ATET}_0}) \\ &- (\underbrace{E[y_U^0|\overline{h}_1, A_1] - E[y_U^0|\overline{h}_1, A_0]}_{\text{spillover on untreated}}) - (\underbrace{E[y_U^0|\overline{h}_1, A_0] - E[y_U^0|\overline{h}_0, A_0]}_{\text{ATEU}_0}) \end{aligned}$$

If the untreated group is truly non-treated, by definition $ATEU_0 = 0$

From the previous equation, we realize that spillover effects for treated and untreated cancel out for DD to recover $ATET_0$.

Alternatively, to recover $ATET_0$ from the DD estimator sufficient conditions are

- Parallel trends (under baseline aggregate conditions)

$$E[y_T^0|\overline{h}_1, A_0] - E[y_T^0|\overline{h}_0, A_0] = E[y_U^0|\overline{h}_1, A_0] - E[y_U^0|\overline{h}_0, A_0]$$

- No spillover effects / SUTVA for $G = \{T, U\}$ for both treated T and untreated U groups

$$E[y_G^1|\overline{h}_1, A_0] = E[y_G^1|\overline{h}_1, A_1]$$
$$E[y_G^0|\overline{h}_1, A_0] = E[y_G^0|\overline{h}_1, A_1]$$

This may imply either no aggregate effects of policy, i.e $A_0 = A_1$, or that the expected outcome of the group G is not sensitive to aggregate conditions for particular realizations of A_0, A_1.

This analysis shows that the standard DD approach typically fails to recover a parameter of interest such as ATET. We may even question if this is the correct parameter to focus on while evaluating the impact of the reform.

8 Conclusions

Considering that time allocations are crucial for household welfare and labor market outcomes, many countries have adopted legal hours regulations such as France, Portugal, Germany, and Chile. After the reduction in legal hours worked in the 1990s in Portugal and France, there has been a resurgence of the debate on regulating time for working in the form of reducing the workweek from 5 to 4 days. However, much of the impact of reducing hours worked is still unknown.

The Chilean case in 2005, which consisted of the reduction of 48 to 45 hours per week, is somewhat a cleaner "natural experiment" but also entails an increase in hourly wages, as the law mandated frozen nominal monthly wages. This paper makes progress in evaluating the impact of the Chilean reform of 2005 using different and complementary empirical strategies.

Following previous studies, we seek to estimate the ATET of the 2005 legal weekly hours reduction on those directly affected, i.e., individuals in the formal private sector working more than 46 weekly hours before 2005, using the rotating panel of the Chilean National Employment Survey (akin to monthly CPS in the US). Compared to an ex ante alike group working 40-45 hours per week, we mostly find no significant effects in several kinds of employment. However, using the Encuesta de Protección Social (EPS), a panel of restrospective work histories, we do find some small negative significant anticipation impact on total employment and private salaried employment.

Several considerations suggest that we adopt an aggregated effect. First, many theoretical models of the labor market, especially those portraying search frictions suggest relevant general equilibrium effects, as private-salaried full-time jobs often impact the outside option of workers. Those kinds of spillovers suggest that the Stable Treatment Unit Survey assumption (SUTVA) is violated in the context of a policy change that affects nearly 60% of the employment. Despite the recent buoyance of theoretical work in DD estimators, relatively few papers address this particular issue (Butts, 2021; Clarke, 2017; Alves et al., 2024) each of those in particular settings. Moreover, as the time span of the micro data is quite limited, we could surmount that limitation by constructing a synthetic panel using ENE data for the period 2000-2008 to estimate the dynamic impact of the policy using local projections Jordà (2005). We find a positive and increasing impact on total employment, with the probability of being employed increasing by 1.9 percentage points in response to the average reduction of 2.1 hours after two years.

To make sense of the results, we construct a structural search and matching model portraying wage bargaining, endogenous self-employment, and endogenous choices of hours subject to the workweek regulation. We estimate the model to match the economy under a 45-hour workweek using the 2009 CASEN survey, obtaining a reasonaby good fit for key moments. We then simulate the economy under the previous policy of 48-hour to obtain a cualitative prediction aligned with macro evidence (local projections) accounting for potential spillover or general equilibrium effects. The 48-hour economy shows lower self-employment, higher market tightness and job arrival rates, wages and productivity. According to our structural model, the reduction to 40 working hours contemplated in the law as of 2028 would have similar effects to those generated by the reduction of hours in 2005. The effect of the policy through the outside option and the selection associated to self-employment and employment endogenous choices explain these results.

All in all, the results suggest that micro-evidence based on traditional design may mask important effects that cannot be discovered using micro data alone. Most of the current micro-evidence available, including ours, suggest that there are small effects for the directly affected groups. Our results show that aggregate data can show quite a different effects so policies advocating hours reduction should proceed with caution if solely based on micro evidence. The macro evidence results match the intuitions derived from a mostly conventional search and matching model in which spillover effects are substantial. The legal hours regulation not only affect workers directly affected by it, but also many other groups in the economy whose relevant outside options are changed through the policy.

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A Graphs

Appendix A ENE (Implementation Effects)

Figure 8: Proportion of salaried workers

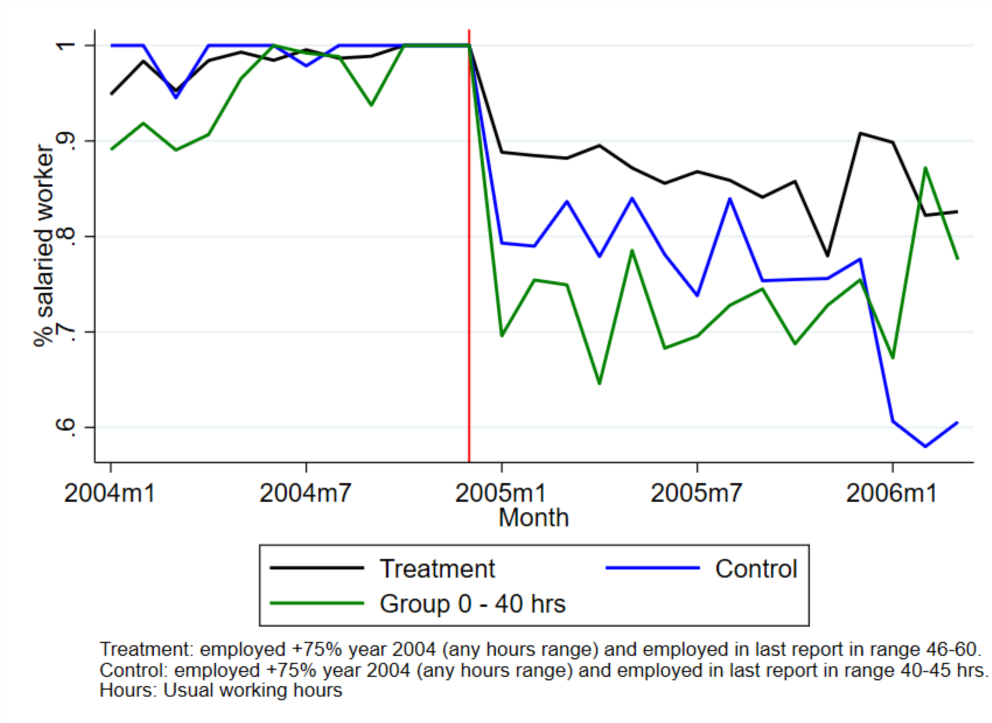


Figure 9: Proportion of unemployed workers

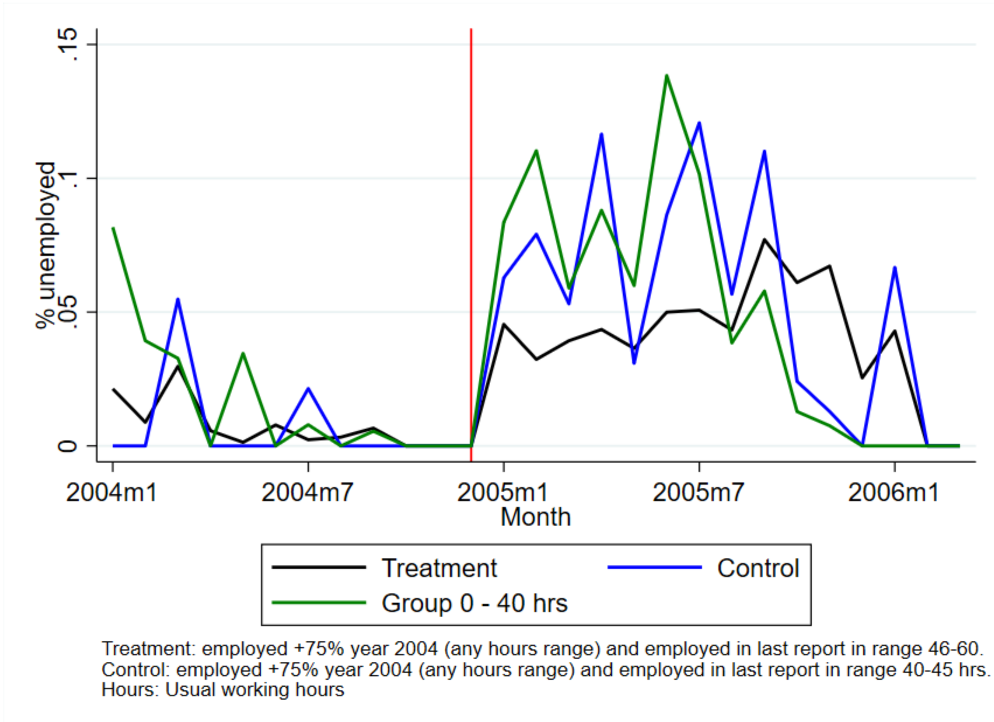
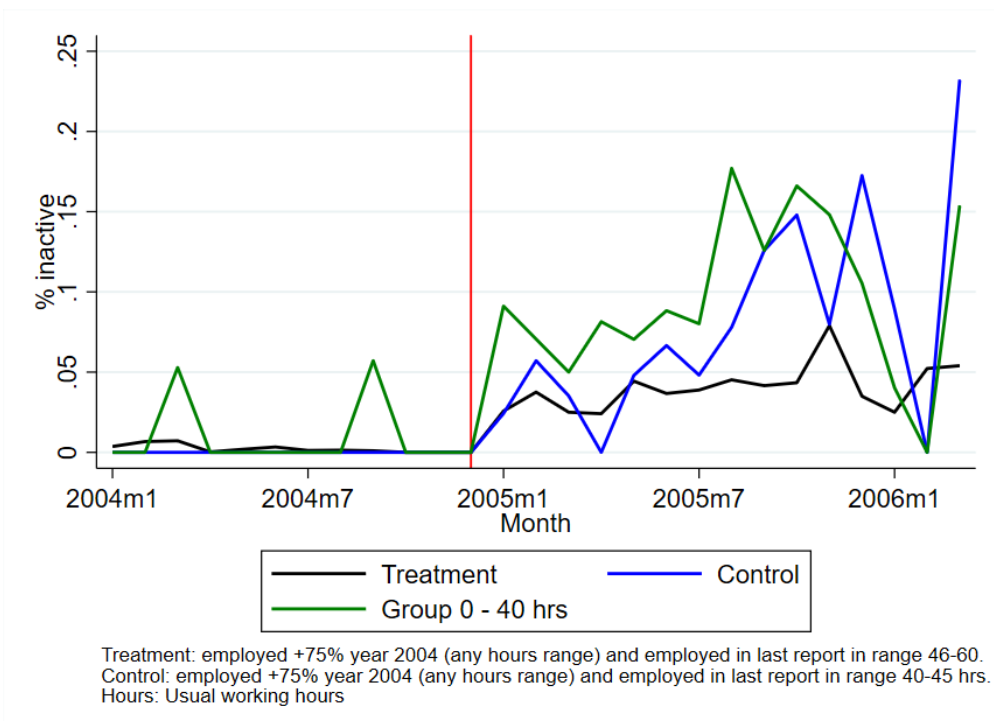


Figure 10: Proportion of inactive workers



Appendix B EPS (Anticipation Effects)

Figure 11: Proportion of salaried workers

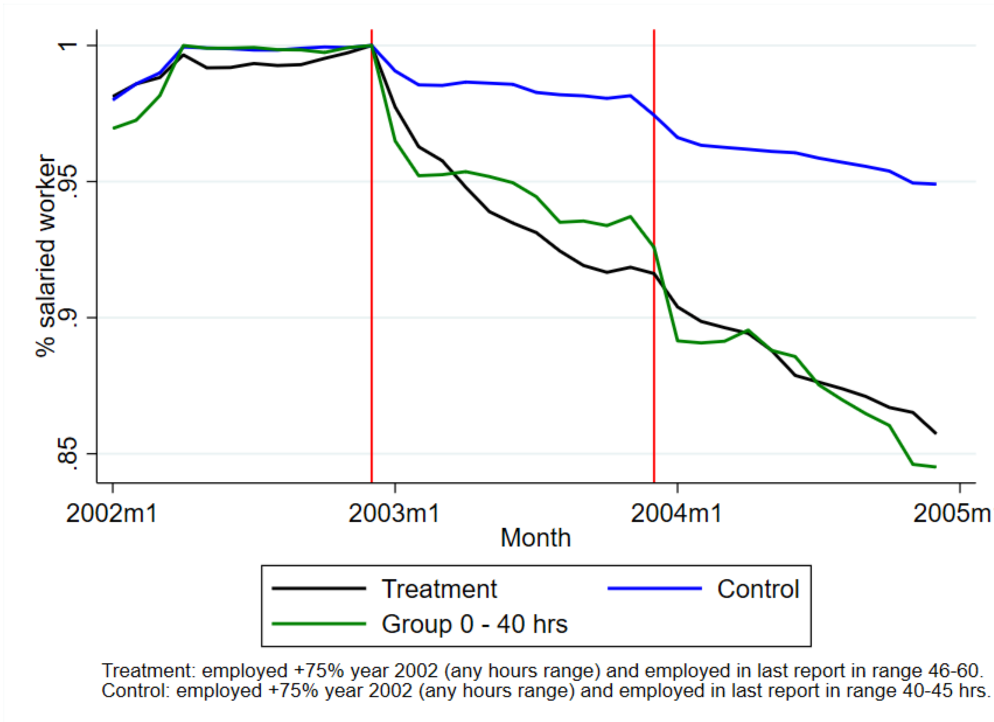


Figure 12: Proportion of unemployed workers

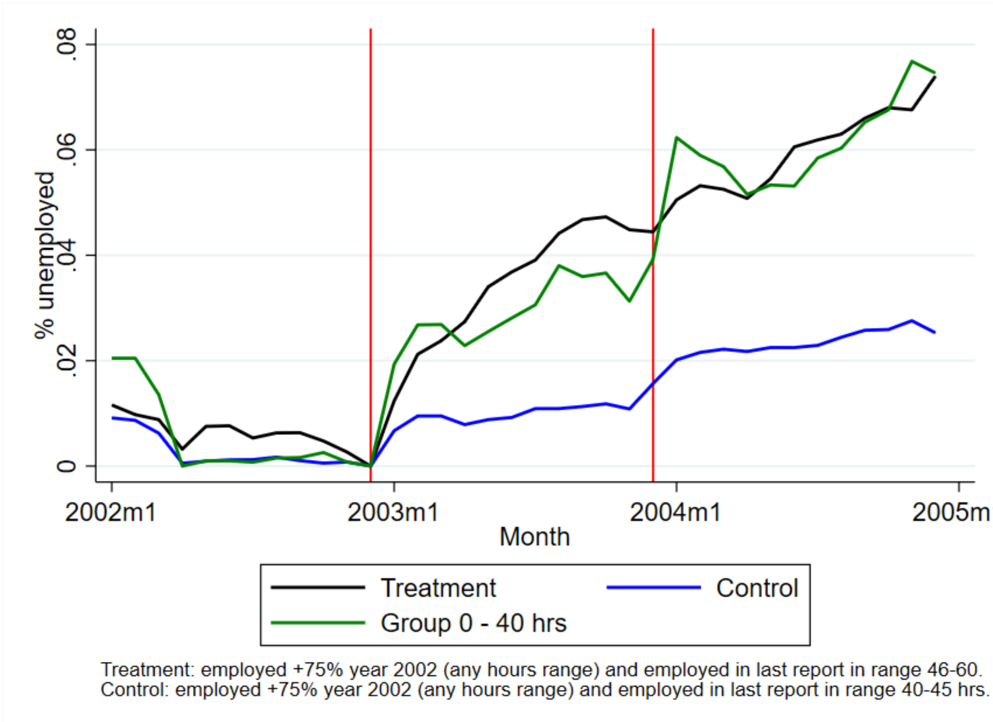
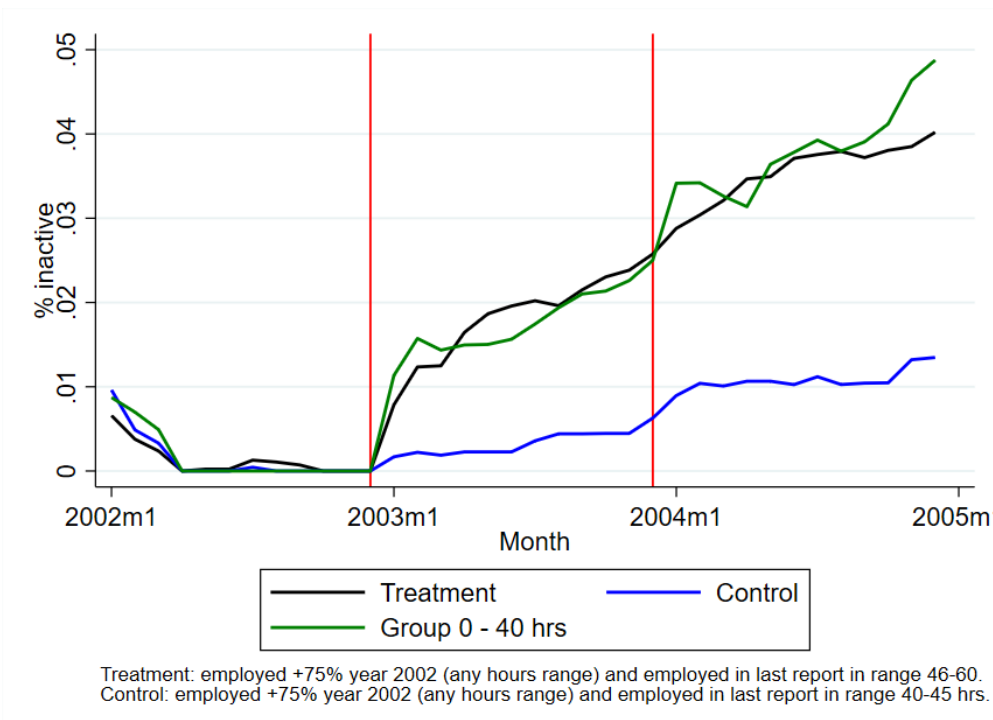


Figure 13: Proportion of inactive workers



B Tables

Appendix A Table 1 with and without Wooldridge

Table 8: Diff-in-diff ATET estimation on usual working hours.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	-4.487	-5.626*	-3.215	-4.290
	(2.915)	(3.297)	(4.114)	(4.695)
R-Squared	0.109	0.062	0.118	0.063
Observations	20620	15453	19504	14622
Number of groups	5334	5315	5042	5024
Mean dep var	43.620	42.548	44.446	43.270
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 9: Diff-in-diff ATET estimation on employed.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 $\times$ Tr 46-60	0.091	0.031	0.040	0.016
	(0.059)	(0.071)	(0.087)	(0.105)
R-Squared	0.053	0.025	0.048	0.023
Observations	20793	15587	19672	14752
Number of groups	5334	5334	5042	5042
Mean dep var	0.950	0.934	0.953	0.938
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 10: Diff-in-diff ATET estimation on salaried worker.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 $\times$ Tr 46-60	0.113*	0.062	-0.015	-0.004
	(0.062)	(0.072)	(0.086)	(0.102)
R-Squared	0.086	0.035	0.079	0.033
Observations	20793	15587	19672	14752
Number of groups	5334	5334	5042	5042
Mean dep var	0.920	0.895	0.925	0.901
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 11: Diff-in-diff ATET estimation on private-sector salaried worker.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	0.159**	0.094	0.078	0.059
	(0.064)	(0.080)	(0.092)	(0.111)
R-Squared	0.102	0.042	0.095	0.041
Observations	20793	15587	19672	14752
Number of groups	5334	5334	5042	5042
Mean dep var	0.909	0.880	0.914	0.887
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 12: Diff-in-diff ATET estimation on public-sector salaried worker.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	-0.046	-0.032	-0.093**	-0.064
	(0.041)	(0.055)	(0.044)	(0.054)
R-Squared	0.023	0.014	0.032	0.018
Observations	20793	15587	19672	14752
Number of groups	5334	5334	5042	5042
Mean dep var	0.011	0.015	0.011	0.014
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 13: Diff-in-diff ATET estimation on self-employed.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 $\times$ Tr 46-60	-0.064	-0.062	0.012	-0.002
	(0.048)	(0.059)	(0.056)	(0.067)
R-Squared	0.028	0.015	0.026	0.011
Observations	20793	15587	19672	14752
Number of groups	5334	5334	5042	5042
Mean dep var	0.026	0.034	0.024	0.031
Prop treatment 46-60	0.892	0.892	0.944	0.944

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: All

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Appendix B Table 1 excluding Professional and Managerial occupational groups

Table 14: Diff-in-diff ATET estimation on usual working hours, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	-6.361*	-8.492**	0.451	-2.921
	(3.334)	(4.158)	(4.528)	(5.429)
R-Squared	0.115	0.065	0.123	0.067
Observations	18703	14000	17899	13407
Number of groups	5030	4978	4793	4746
Mean dep var	43.521	42.349	44.241	42.982
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 15: Diff-in-diff ATET estimation on employed, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	0.123*	0.047	0.170*	0.098
	(0.069)	(0.092)	(0.094)	(0.116)
R-Squared	0.061	0.028	0.054	0.026
Observations	18861	14124	18053	13528
Number of groups	5032	4995	4795	4763
Mean dep var	0.943	0.925	0.947	0.930
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 16: Diff-in-diff ATET estimation on salaried worker, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	0.130*	0.050	0.108	0.071
	(0.074)	(0.088)	(0.098)	(0.118)
R-Squared	0.097	0.039	0.087	0.037
Observations	18861	14124	18053	13528
Number of groups	5032	4995	4795	4763
Mean dep var	0.913	0.885	0.919	0.893
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 17: Diff-in-diff ATET estimation on private-sector salaried worker, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	0.140*	0.057	0.124	0.080
	(0.075)	(0.089)	(0.102)	(0.118)
R-Squared	0.108	0.043	0.099	0.041
Observations	18861	14124	18053	13528
Number of groups	5032	4995	4795	4763
Mean dep var	0.906	0.876	0.912	0.884
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 18: Diff-in-diff ATET estimation on public-sector salaried worker, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	-0.011	-0.007	-0.016	-0.009
	(0.020)	(0.014)	(0.036)	(0.014)
R-Squared	0.018	0.007	0.025	0.007
Observations	18861	14124	18053	13528
Number of groups	5032	4995	4795	4763
Mean dep var	0.007	0.009	0.007	0.009
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

Table 19: Diff-in-diff ATET estimation on self-employed, excluding Professional and Managerial occupational groups.

	Control A		Control B	
	No Wooldridge	With Wooldridge	No Wooldridge	With Wooldridge
Post JA05 × Tr 46-60	-0.090	-0.064	0.014	0.006
	(0.072)	(0.085)	(0.062)	(0.075)
R-Squared	0.032	0.016	0.029	0.013
Observations	18861	14124	18053	13528
Number of groups	5032	4995	4795	4763
Mean dep var	0.027	0.035	0.025	0.033
Prop treatment 46-60	0.915	0.916	0.956	0.957

Standard errors clustered at the individual level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Hours: Usual working hours. Sample: Non-Professional and Non-Managerial

Control A: employed +75% last year (any hours range) and employed in last report in range 0-45 hrs

Control B: employed +75% last year (any hours range) and employed in last report in range 40-45 hrs

Treatment: employed +75% last year (any hours range) and employed in last report in range 46-60 hrs

C Model derivation details

Appendix A Wage and hours worked determination

The wage and hours bargaining problem is

$$\max_{w,h} \left(E(x) - Q\right)^{\beta} \left(J(x) - V\right)^{1-\beta} \tag{A.1}$$
$$s.to \quad h \leq \bar{h}$$

This can be expressed also as

$$\max_{w,h} \beta \log\left(E(x) - Q\right) + (1-\beta)\log\left(J(x) - V\right)$$
$$s.to \quad h \leq \bar{h} \leftarrow mult : \gamma$$

$$L = \beta \log\left(E(x) - Q\right) + (1-\beta)\log\left(J(x) - V\right) + \gamma\left(h - \bar{h}\right)$$

First-order conditions (FOC) are

$$w : \frac{\beta}{E(x) - Q}\frac{\partial\left[E(x) - Q\right]}{\partial w} + \frac{1-\beta}{J(x) - V}\frac{\partial\left[J(x) - V\right]}{\partial w} = 0$$
$$h : \left[\frac{\beta}{E(x) - Q}\frac{\partial\left[E(x) - Q\right]}{\partial h} + \frac{1-\beta}{J(x) - V}\frac{\partial\left[J(x) - V\right]}{\partial h}\right] + \gamma = 0$$
$$\gamma\left(h - \bar{h}\right) = 0$$

Note that:

$$(\rho + \eta) E(x) - (\rho + \eta) Q = wh - e(h) + \eta Q - (\rho + \eta) Q$$
$$E(x) - Q = \frac{wh - e(h) - \rho Q}{\rho + \eta}$$

$$(\rho + \eta)\left[J(x) - V\right] = (x - w) h + \eta V - (\rho + \eta)V$$
$$= (x - w) h - \rho V$$
$$J(x) - V = \frac{(x - w) h - \rho V}{\rho + \eta}$$

Solving the FOC for w yields

$$\frac{\beta}{E(x) - Q}\frac{\partial\left[E(x) - Q\right]}{\partial w} = -\frac{1-\beta}{J(x) - V}\frac{\partial\left[J(x) - V\right]}{\partial w}$$

Therefore:

$$\frac{\beta\,(\rho+\eta)}{wh-e(h)-\rho Q}\frac{h}{\rho+\eta} = -\frac{(1-\beta)\,(\rho+\eta)}{(x-w)\,h-\rho V}\frac{-h}{\rho+\eta}$$
$$\frac{\beta}{wh-e(h)-\rho Q} = \frac{(1-\beta)}{(x-w)\,h-\rho V}$$
$$\beta\,[(x-w)\,h-\rho V] = (1-\beta)\,[wh-e(h)-\rho Q]$$

Using the free entry condition, i.e. $V=0$

$$\beta\,(xh-wh) = (1-\beta)\,(wh-e(h))-(1-\beta)\,\rho Q$$
$$\beta xh = wh-(1-\beta)\,[e(h)+\rho Q]$$
$$wh = \beta xh+(1-\beta)\,[e(h)+\rho Q]$$
$$w = \beta x+(1-\beta)\,\frac{[e(h)+\rho Q]}{h} \tag{A.2}$$

Recall that:

$$E(x)-Q = \frac{wh-e(h)-\rho Q}{\rho+\eta}$$

$$J(x)-V = \frac{(x-w)\,h-\rho V}{\rho+\eta}$$

Solving the FOC for h in case of an interior solution yields

$$\frac{\beta\,(\rho+\eta)}{wh-e(h)-\rho Q}\left[\frac{w-e'(h)}{\rho+\eta}\right] = -\frac{(1-\beta)\,(\rho+\eta)}{(x-w)\,h-\rho V}\frac{(x-w)}{\rho+\eta}$$
$$\frac{\beta\,[w-e'(h)]}{wh-e(h)-\rho Q} = -\frac{(1-\beta)\,[x-w]}{(x-w)\,h-\rho V}$$

Using the free entry condition, $V=0$,

$$\beta\,[w-e'(h)]\,[(x-w)\,h] = -\,(1-\beta)\,[x-w]\,[wh-e(h)-\rho Q]$$
$$\beta\,[w-e'(h)]\,h = -\,(1-\beta)\,[wh-e(h)-\rho Q]$$
$$-\beta e'(h)h = -wh+(1-\beta)\,[e(h)-\rho Q]$$
$$\beta e'(h)h = wh-(1-\beta)\,[e(h)-\rho Q]$$

Using the wage equation, we obtain

$$\begin{aligned}
\beta e'(h)h &= \left[\beta x + (1-\beta)\,\frac{e(h)+\rho Q}{h}\right] h - (1-\beta)\,[e(h)-\rho Q] \\
\beta e'(h)h &= \beta x h + (1-\beta)\,[e(h)+\rho Q] - (1-\beta)\,[e(h)-\rho Q] \\
\frac{e'(h)h}{h} &= x \\
e'(h) &= x
\end{aligned}$$

Taking the isoelastic cost function $e(h) = \frac{\epsilon}{1+\nu}h^{1+\nu}$, then $e'(h) = \epsilon h^{\nu}$. We obtain

$$h = \left[\frac{x}{\epsilon}\right]^{\frac{1}{\nu}}$$

In the wage equation:

$$\begin{aligned}
w(x) &= \beta x + (1-\beta)\left[\frac{\frac{\epsilon}{1+\nu}h^{1+\nu} + \rho Q}{h}\right] \\
&= \beta x + (1-\beta)\left[\frac{\epsilon}{1+\nu}h^{\nu} + \frac{\rho Q}{h}\right] \\
&= \beta x + (1-\beta)\left[\frac{x}{1+\nu} + \left[\frac{\epsilon}{x}\right]^{\frac{1}{\nu}}\rho Q\right] \\
&= \left[\frac{1+\beta\nu}{1+\nu}\right] x + (1-\beta)\left[\frac{\epsilon}{x}\right]^{\frac{1}{\nu}}\rho Q
\end{aligned}$$

Using the slackness condition

$$\begin{aligned}
\beta e'(h)h &> wh - (1-\beta)\,[e(h)-\rho Q] \\
e'(h) &> x \\
\epsilon \bar{h}^{\nu} &= \tilde{x} > x
\end{aligned}$$

Therefore we obtain the results

$$h(x) = \begin{cases} \left[\frac{x}{\epsilon}\right]^{\frac{1}{\nu}} & x < \epsilon \bar{h}^{\nu} \\ \bar{h} & x \geq \epsilon \bar{h}^{\nu} \end{cases}$$

$$w(x) = \begin{cases} \left[\frac{1+\beta\nu}{1+\nu}\right] x + (1-\beta)\left[\frac{\epsilon}{x}\right]^{\frac{1}{\nu}}\rho Q & x < \epsilon \bar{h}^{\nu} \\ \beta x + (1-\beta)\left[\frac{\epsilon}{1+\nu}\bar{h}^{\nu} + \frac{\rho Q}{\bar{h}}\right] & x \geq \epsilon \bar{h}^{\nu} \end{cases}$$

Appendix B Free entry condition

$$\kappa = \lambda(\theta) \int_x \max\left\{J(x), 0\right\} dF(x)$$
$$\kappa / \int_x \max\left\{\frac{h(x)\left(x - w(x)\right)}{\rho + \eta}, 0\right\} dF(x) = m\left(1/\theta, 1\right)$$

Taking a Cobb-Douglas matching function $m(u + s, v) = (u + s)^{\gamma} v^{1-\gamma}$ then

$$\begin{aligned}\lambda(\theta) &= \frac{m(u+s,v)}{v} = \frac{(u+s)^{\gamma}v^{1-\gamma}}{v} \\ &= (u+s)^{\gamma}v^{-\gamma} = \left(\frac{u+s}{v}\right)^{\gamma} = \frac{1}{\theta^{\gamma}}\end{aligned}$$

$$\lambda(\theta)\theta = \frac{\theta}{\theta^{\gamma}} = \theta^{1-\gamma}$$

$$\kappa / \int_x \max\left\{\frac{h(x)\left(x - w(x)\right)}{\rho + \eta}, 0\right\} dF(x) = \frac{1}{\theta^{\gamma}}$$

$$\theta = \left[\frac{\int_x \max\left\{\frac{h(x)(x-w(x))}{\rho+\eta}, 0\right\} dF(x)}{\kappa}\right]^{1/\gamma}$$

Appendix C Steady State

$$\lambda(\theta)\theta\left[1 - F(x_u^*)\right] u = \eta G(y^*) e$$
$$\left[\delta\lambda(\theta)\theta\left[1 - F(x_s^*(y))\right] + \phi\right] s(y) = \eta\left[1 - G(y^*)\right] e$$
$$u + s + e = 1$$

$$\int_y s(y) dG(y|y > y^*) = s = \eta\left[1 - G(y^*)\right] e \int_y \frac{1}{\delta\lambda(\theta)\theta\left[1 - F(x_s^*(y))\right] + \phi} dG(y|y > y^*)$$

$$s = h_{es}h_s e$$

$$\begin{bmatrix} h_u & 0 & -h_{eu} \\ 0 & 1 & -h_{es}h_s \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ s \\ e \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$
\begin{aligned}
h_u u &= h_{eu} e \\
s &= h_{es} h_s e \\
h_u u + s &= \left(h_{eu} + h_{es} h_s\right) e \\
\frac{h_u}{h_{eu} + h_{es} h_s} u + \frac{1}{h_{eu} + h_{es} h_s} s &= e
\end{aligned}
$$