Subsidizing Labor Hoarding in Recessions:
The Employment & Welfare Effects of Short Time Work

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October 24, 2018

Abstract

The Great Recession has seen a revival of interest in policies encouraging labor hoarding by firms. Short time work (STW) policies, which consist in offering subsidies for hours reductions to workers in firms experiencing temporary shocks, are the most emblematic of these policies, and have been used aggressively during the recession. Yet, very little is known about their employment and welfare consequences. This paper leverages unique administrative social security data from Italy and quasi-experimental variation in STW policy rules to offer compelling evidence of the effects of STW on firms' and workers' outcomes, and on reallocation in the labor market. Our results show large and significant negative effects of STW treatment on hours, but large and positive effects on headcount employment. Results also show that employment effects disappear when the program stops, and that STW offers no long term insurance to workers. Finally, we identify the presence of significant negative reallocation effects of STW on employment growth of untreated firms in the same local labor market. We develop a simple conceptual framework to rationalize this empirical evidence, from which we derive a general formula for the optimal STW subsidy that clarifies the welfare trade-offs of STW policies. Calibrating the model to our empirical evidence, we conduct counterfactual policy analysis and show that STW stabilized employment during the Great Recession in Italy, and brought (small) positive welfare gains.

1 Introduction

The Great Recession has generated a significant revival of interest in policies destined at encouraging labor hoarding by firms during downturns (e.g. Yagan [2017], Giroud and Mueller [2017]). Short time work programs (STW), which are subsidies for temporary reductions in the number of hours worked, is the most emblematic of such policies, and has been aggressively used during the Great Recession, especially in European countries. The fraction of employees on STW in 2009 reached 7% in Belgium, close to 5% in Germany and 4% in France.[1] In Italy, according to the social security data, 4.6% of the workforce was in STW in 2013, for a cost of .5% of GDP. This revival of interest is also palpable in the U.S., where state STW programs have been actively promoted by the Job Creation Act of 2012. In 2016, more than 28 U.S. states had implemented their own STW program.[2]

But what is behind this STW craze? Do we know that it is effective in stabilizing employment? Is it helping firms hold onto their productive workers? Is it an effective way to provide insurance to workers? More effective than unemployment insurance (UI) for instance? More fundamentally, do we know anything about its welfare implications? What sources of inefficiencies are we trying to correct with STW? If we believe that hours or employment are not optimally set in the labor market, how can STW deal with these inefficiencies? Are we not creating additional inefficiencies with these programs, by keeping workers in unproductive firms, preventing efficient reallocation of labor?

Despite STW being a key element to the countercyclical policy toolkit, and one of the main active labor market policy during downturns, we are completely at a loss to answer these fundamental questions: we know close to nothing about the effects of STW, and its welfare consequences. This all the more surprising given the large literature devoted to the use of other insurance programs such as UI over the business cycle (e.g. Schmieder, von Wachter and Bender [2012], Landais, Michaillat and Saez [2018a], Landais, Michaillat and Saez [2018b], Kekre [2016]).

There are however three simple reasons that explain the very limited knowledge that we have of the effects and desirability of STW. The first reason is a critical lack of firm or individual level administrative data on STW.[3] The literature on STW had to mainly resort to cross country analysis (e.g. Audenrode [1994], Boeri and Brücker [2011], Cahuc and Carcillo [2011]). But even in the presence of firm level data, the second issue lies in the lack of credible sources of identification of STW treatment.[4] Most papers therefore rely on the structure of calibrated models to analyze the effects of STW on workers and firms (Tilly and Niedermayer [2016], Cooper, Meyer and Schott

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[1]Hijzen and Martin [2013]. Cahuc, Kramarz and Nevoux [2018]

[2]U.S. Department of Labor Office of Unemployment Insurance [2016].

[3]As a matter of example, the German social security administration (IAB) does not collect data on STW. Most STW applications and reports are sent in a paper format to the Federal Employment Agency, and are not digitized. Only a sample of these reports has been digitized for the Nuremberg metropolitan area for years 2008 to 2010 and matched to IAB data (Tilly and Niedermayer [2016]).

[4]In most countries with large STW programs in place, like Germany or France for instance, there is no variation in a firm's eligibility to take up STW. This severely complicates identification, with no obvious method to control for the selection of firms into STW take up.

[2017]). Alternatively, a few studies have tried to find instruments for the take up of STW, but their results have not enabled to reach any consensus.[5] Even if we were to have some credible estimates of the effects of STW on workers' and firms' outcomes, the third issue is the lack of a simple, tractable yet general conceptual framework to rationalize the empirical evidence and feed these estimates back into a welfare evaluation that would make transparent the trade-offs implied by STW policies.[6]

This paper contributes to our understanding of STW by addressing these three limitations. It relies on uniquely rich administrative data on STW from Italy. It uses the presence of variation in eligibility rules across firms to provide compelling evidence of the causal impact of STW on firms' and workers' outcomes. And it offers a simple and general conceptual framework that maps to our empirical results to transparently assess the welfare consequences of STW programs.

Our data comes from the Italian social security administration (INPS) and covers the universe of Italian employer-employee matches in the private sector, and the universe of all social security and transfer payments in Italy, from 1983 to 2015. Besides granular information on firms and workers' histories, it provides detailed information on eligibility, applications and authorizations of the universe of STW episodes at both the firm and individual levels from 2005 to 2015. This data, combined with the specificities of the Italian STW program, which creates variation in eligibility across firms, allows us to provide causal evidence of the effects of STW. Identification stems from the interaction between two sources of variation in eligibility: INPS codes and firm size. First, we exploit the fact that within 5-digit industries, certain firms, defined by particular INPS codes, are eligible while others are not, because of the particular interpretation of the STW Law that was given by INPS in a circular dating back to the 1970s. While this variation in STW access across otherwise very similar firms appears exogenous to economic conditions at such fine level today, we use the additional requirement that firms must be above a certain full-time equivalent size threshold to be eligible for the program. This enables us to test and control for the possibility that differential time shocks affected eligible and non-eligible INPS codes within 5-digit industries during the recession. We further provide multiple robustness checks for the validity of our approach. In particular, we show that our approach is not confounded by manipulation of size or INPS codes, nor by any other change in regulations at the main eligibility size threshold.

Our results demonstrate that STW has large and significant effects on firms' employment at both the intensive and extensive margin. Compared to counterfactual firms, firms treated by STW experience a 40% reduction in hours worked per employee, and a similar magnitude increase in the number of employees in the firm, with no discernible effect on wage rates. Unpacking the

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[5]Most studies instrument STW take up during the recession with the prior experience of firms with the program (e.g. Boeri and Brücker [2011], Cahuc and Carcillo [2011], Hijzen and Martin [2013]) and find competing results. Recently, Cahuc, Kramarz and Nevoux [2018] offer a credible and compelling IV strategy in the French context. They instrument STW take up using the proximity of a firm to other firms having used STW before recessions. They also use as an alternative instrument response time variation in the administrative treatment of STW applications across French departments. They find, similar to our results, large and significant employment effects of STW treatment.

[6]While a small theoretical literature shows (not surprisingly) that STW may distort both hours (Burdett and Wright [1989]), and the allocation of workers across firms, thus reducing output (Cooper, Meyer and Schott [2017]), there is no clear view of the conditions under which STW programs might be socially desirable and improve welfare.

full dynamics of treatment effects, we show that these employment effects are temporary, and immediately disappear once STW treatment stops. On the workers side, we similarly find that treatment effects are all concentrated in the short run. STW has immediate positive effects on employment probability, but negative effects on hours, and a positive effect on total earnings and transfers. But these effects disappear after treatment, so that STW provides no significant insurance to workers in the medium or long run. In fact, two years after treatment, there is no significant differences in the employment probability, earnings, and total income of workers who were treated by STW and workers who were counterfactually laid-off.

We then analyze the selection of firms into STW and the heterogeneity in the treatment effects of the program, to shed light on the mechanisms behind the temporary nature of the average estimated effects and the lack of long term insurance for workers. In particular, we show that firms that were at the bottom of the productivity distribution before the Recession are three times more likely than higher productivity firms to take up STW during the Recession and that employment effects for them are significantly smaller. This clearly suggests that STW is predominantly targeting firms that have permanently lower productivity and helps explain why keeping workers in these firms does not entail significant long term benefits. More importantly, this suggests that by keeping workers in low productivity firms, STW may have significant negative reallocation effects in the labor market.

To investigate these claims, we leverage the rich spatial variation available in Italy across more than 600 local labor markets (LLM) and estimate how an increase in the fraction of workers treated by STW in a LLM affects employment outcomes of non-treated firms. We instrument variation in the intensity of STW treatment across LLM by the average yearly fraction of eligible workers in the LLM based on the interaction between firm size and INPS codes in the pre-recession period, controlling for a rich set of firm and LLM characteristics. We provide various placebo tests confirming the validity of our IV strategy. Our results provide compelling evidence of the presence of equilibrium effects of STW within labor markets. We show that STW significantly decreases the employment growth and inflow rates of non-treated firms, and has a significant negative impact on TFP growth in the labor market.

We finally provide a tractable search and matching framework that rationalizes these empirical findings, and maps our estimates into a transparent welfare evaluation of STW. While remaining general, the model adds a series of key ingredients that prove critical to evaluate the arguments put forward in favor or against the existence of STW programs. First, workers are risk averse and are imperfectly insured so that insurance against the incidence of productivity shocks on workers' earnings is socially desirable. The model allows firms, which are subject to (idiosyncratic and/or aggregate) productivity shocks, to adjust labor inputs along both the intensive (hours) and extensive (employment) margin.[7] Wages and hours are negotiated between workers and firms,

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[7]In that sense, our model is related to Cooper, Meyer and Schott [2017], but with two important departures: first workers are risk averse and insurance markets are incomplete, which provides a rationale for social insurance. And second, the hours constraint, which creates potential inefficiencies in employment is endogenous rather than exogenous.

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to split the surplus generated by matches in a frictional labor market. And hours adjustments are therefore constrained by the outside options of workers.[8] More generally, wage and hours schedules may not always guarantee that hours and employment are set at their socially efficient level, opening the potential need for a government intervention to stabilize employment and hours.[9] In this environment, STW policies, by affecting equilibrium in the labor market, naturally create reallocation effects between high and low productivity firms.

Many arguments have been put forward in the public debate in favor or against STW. STW provides insurance to workers, it provides insurance to firms against the costs of replacing workers, it mitigates hours and wage rigidities that may prevent optimal labor adjustments, it stabilizes employment, it inefficiently reallocates labor towards low productivity firms, etc. Thanks to its generality, our model encompasses an array of previous frameworks used in the small theoretical literature on STW, and enables to review within one single framework most of these important arguments. We contribute by clarifying the conditions under which STW "works", i.e. induces firms hit by productivity shock to take up the program, and increase their employment. In particular we show that wage rigidity critically amplifies the employment responses to STW.

Importantly, our model is directly related to the public finance literature on optimal policies in equilibrium models of the labor market (see for instance Landais, Michaillat and Saez [2018a] and Michaillat and Saez [2017]). In the spirit of this sufficient statistics literature, we use the model to provide a general formula for the optimal generosity of STW subsidies which clarifies the key welfare tradeoffs of STW programs. The main insight is that optimal STW not only balances the insurance value of the subsidy with its fiscal externality but also needs to account for two additional sources of inefficiencies: first employment may be inefficient due to the frictional nature of the labor market, and second, equilibrium hours may also not be at their socially optimal level due to the missing market for hours. STW will entail positive welfare gains when equilibrium employment is suboptimally low, and hours suboptimally high, and our formula offers a clear representation of these hours and employment inefficiency terms. The advantage of this approach is that the formula, and the key tradeoffs underpinning it, remain the same irrespective of the exact structure and primitives of the underlying model. In that sense, our formula is robust to the way wages and hours are determined in the model, to the specification of the costs of replacing or firing workers, to the presence of specific human capital, to various sources of hours or wage rigidity, to the presence of liquidity constraints, etc. Furthermore, our approach offers the possibility to conduct a local welfare calibration using our reduced form estimates, which suggests that in the current Italian context, both the fiscal externality and the insurance value of STW are high, and that the marginal welfare gains of further increases in STW are small as the employment and hours inefficiencies are equally large but of opposite sign.

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[8]As in Braun and Brügemann [2014], this means that STW may correct inefficiencies created by the unemployment insurance system.

[9]Note that we do not impose restrictions on the matching environment. Assuming directed search, as in Cahuc, Kramarz and Nevoux [2018] for instance, would guarantee that hours and employment are always socially efficient, leaving no role for STW to correct potential inefficiencies in employment and hours over the business cycle.

Finally, we use a calibrated version of the model to run non-marginal counterfactual analysis and quantify the welfare effects of removing STW. This analysis confirms that the welfare gains of further increases in the generosity of STW are small, but the value of having STW is significantly positive. In the absence of any STW subsidy, the unemployment level would have been almost 2 percentage points higher during the recession, and total TFP about 2% higher, but at a total welfare cost of about 2%. We also use the calibrated model to explore various counterfactual scenarii and gain further insights on the effects of STW outside the specific context of Italy, where the Great Recession transformed into a long, protracted shock. We show that the immediate employment effects of STW are significantly larger (around 20% to 40%) when the aggregate shock is temporary than when it is permanent, as firms' desire for labor hoarding is much greater for temporary shocks, especially when the cost of replacing workers is high, and when the magnitude of the aggregate shock is large. This suggests that STW might have been much more effective in the German context than in Italy during the Great Recession.

The remainder of the paper is organized as follows. Section 2 describes the Italian STW institutions and the data. Section 3 presents the identification strategy and our estimates of the effects of STW on firms outcomes. We explore in section 4 the corresponding effects of STW on the short run and long run outcomes of workers. Section 5 investigates selection into the program and heterogeneity in its treatment effects before presenting clear evidence of the spillover effects of the program on untreated firms. Section 6 develops the model and explores the welfare implications of our findings.

2   Institutional Background & Data

2.1   The Italian *Cassa Integrazione Guadagni* (CIG)

The Italian Cassa Integrazione Guadagni (CIG) was created in 1941. It represents, with the German *Kurzarbeit*, one of the oldest, largest and most comprehensive short-time work programs in the world. It was heavily used during the latest recession: in 2013, almost 5% of the Italian workforce was on STW, for a cost of roughly .5% of Italian GDP. This massive expansion of STW take-up makes Italy the perfect laboratory to analyze the employment and welfare consequences of STW during the Great Recession.

CIG is composed of three programs: Cassa Integrazione Guadagni Ordinaria (CIGO), Cassa Integrazione Guadagni Straordinaria (CIGS) and Cassa Integrazione Guadagni in Deroga (CIGD). We focus throughout the paper on the second program, CIGS, which is the main pillar of STW used in recessions.[10]

CIGS rules are quite standard among STW programs, and make it a good example of most of the programs implemented across OECD countries. CIGS targets firms experiencing economic shocks,

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[10]CIGO is restricted to small transitory shocks or accidents involving forced reduction of activity (e.g. adverse weather conditions, earthquakes, power cuts). It is restricted to the manufacturing sector and has a maximum duration of 13 weeks. CIGD is a smaller additional program created in 2009, administered at the local level and granted ad-hoc on the basis of regional decrees.

broadly defined: it can be a demand or revenue shock, a company crisis, a need for restructuring or reorganization, an illiquidity or insolvency issue, etc. CIGS is a subsidy for partial or full-time hour reductions, replacing approximately 80% of the earnings forgone by the worker due to hours not worked.[11] The subsidy is available to workers in the private sector and is administered by the Italian Social Security (INPS). The subsidy is remitted directly to the workers. Firms intending to use the program must file an application to the Social Security or the Ministry of Labor, providing a justification of economic need and a recovery plan.[12] Once authorized, the usage of CIG is subject to weak conditionality requirements for both firms and workers: there are no provisions for compulsory training nor prohibitions of dismissal by firms, and no job-search requirements for employees. The cost to firms of putting workers on CIGS is minimal: they pay a fee to INPS equal to 3 to 4.5% of the total amount of the subsidy to workers.[13] CIGS is otherwise financed via ordinary payroll contributions. The duration of the program is up to 12 months, with limited possibilities of extensions. Utilization of the program need not be on a continuous basis, but cannot exceed a maximum duration of 36 months – including extensions – over 5-year periods that are fixed and defined by the law. In practice, almost all firms use CIGS for exactly 12 months, with the median and average durations of CIGS take-up both almost equal to 52 weeks.

One of the specificities of CIGS is the presence of various provisions of the law that create quasi-exogenous variation in eligibility across firms, offering the unique possibility of identifying the causal effect of short-time work programs on firm and individual outcomes. This is remarkable as most STW programs like the German *Kurzarbeit* or the French STW, provide little to no variation in eligibility across firms, making it complicated to identify the causal effect of STW in these contexts (Cahuc, Kramarz and Nevoux [2018]). We exploit the fact that a firm's eligibility for CIGS depends in particular on two dimensions: an INPS specific code called "contributory regime" and the size of the firm prior to filing an application.

Contributory regimes (or INPS codes) are created by combining 5-digit industry codes and 333 different "codice autorizzazione".[14] Eligibility of each INPS code to CIGS is determined by a circular of the Ministry of Labor translating the provisions of the Law on Cassa Integrazione, and made operational by INPS, dating back to the 1970s. As a consequence, within fine-grained 5-digit industry codes (594 industries), there is variation in CIGS eligibility across otherwise very

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[11]Hours not worked are computed against the regular hours stipulated in the labor contract. The normal weekly working hours are 40 in Italy. There is almost no variation in the replacement rate of the subsidy across workers. If a firm is eligible, all workers with at least 90 days of tenure are eligible to be put on CIGS, except for apprentices and top executives of the firm. Firms are free to decide the amount of hours reductions they request, i.e. there is no minimum or maximum amount of hours reduction in the CIGS program.

[12]Using data on CIGS applications and authorizations, we found that in practice, applications are never rejected: 99.99% of applications are authorized by the Ministry of Labor.

[13]The fee is 3% for firms with up to 50 employees and 4.5% for larger firms. In 2015, a reform introduced an experience rating component to the costs of CIGS to the employer by making the fee an increasing function of the amount of subsidized hours.

[14]The "codice autorizzazione" is an administrative code used by INPS that, in combination with the 5-digit industry code, defines the various programs and contributions a firm is eligible to or subject to. The combination of 5-digit industry codes and "codice autorizzazione" creates an INPS code that allows to univocally identify the contributory regime and CIGS eligibility of any given firm.

similar firms, due to regulations from the Ministry of Labor that are quite plausibly exogenous to economic conditions at such fine level today. To provide just a few concrete examples: within the 5-digit industry codes 11306, 11307 and 11308, which are firms in construction specialized in the installation of electrical machinery, only those with codice autorizazzione 3N are eligible; within the 5-digit code 10106, which are firms that produce seeds and beans, only firms with codice autorizzazione 3A are eligible.

Besides INPS codes, a firm eligibility to CIGS depends on its size being above a certain threshold. This variation in eligibility across firms of different sizes allows to use non-eligible firms within INPS codes to test and control for differential time shocks across eligible vs non eligible INPS codes. The main size requirement is that a firm must have employed on average more than 15 employees in full-time equivalent (FTE) units in the six months prior to the application.[15] For some industries in the retail sector, the size requirement differs, and is set to 50 FTE. Note that employment legislation regulating dismissals also apply in Italy when a firm reaches 15 employees within a single establishment or municipality, or 60 employees in the firm in Italy as a whole.[16]

We explain in section 3.1 how these sources of variation in eligibility across INPS codes and firm size can be combined to identify the effects of CIGS on firms and workers.

2.2 Data

We use administrative data from INPS on the universe of employer-employee matches and social security payments in the private sector in Italy from 1983 to 2015. The data includes detailed information on workers' demographics, working histories, participation in all social assistance and social insurance programs. It also provides detailed information on firm characteristics such as employment, labor-force composition and industry. Most importantly, starting from 2005, the data provides information on eligibility, applications, authorizations, duration and payments of the Italian short-time work program at the individual and firm level. We linked the administrative archives to firm-level balance-sheet data from CERVED via a unique identifier. CERVED is a firm register containing balance sheet information of all incorporated limited liability companies in Italy. The balance-sheet information covers roughly 50% of firms in the administrative records and enables to create various measures of productivity and credit constraints.

We define STW events at the firm level as any month in which a STW episode is reported in the INPS records, which is also authorized according to the authorization data. When aggregating at the annual level, an event is defined as having at least one STW episode during the year. Eligibility status is defined dynamically using INPS codes and based on the maximum 6-month average FTE firm size in each year.[17]

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[15]To be precise, eligibility to CIGS, and therefore eligibility requirements, all apply at the establishment level. INPS codes are also establishment specific. When we refer to firms throughout the paper, we mean "establishments". We restrict our baseline sample to single establishment firms.

[16]In section 3.3, we explain and provide multiple evidence that our approach is robust to the variation in dismissal costs at the 15FTE threshold. We use in particular multi-establishments firms that are always subject to the dismissal cost regulation.

[17]The FTE size measure relevant for establishing CIGS eligibility is computed considering all employees, including

To define intensive measures of employment, we leverage detailed weekly level information on whether a worker was working full-time or part-time. When working part-time, we have information on the percentage of part-time work. We use this information to create a measure of hours worked for each worker. We assign 40 hours per week to full-time workers, and weight hours for part-time work using the percentage of part-time work, assuming a corresponding full-time contract of 40 hours.

Our main sample of analysis is a balanced panel of all ever-active private sector firms that ever reach an average 6-month full-time equivalent firm size between 5 and 25 in the period 2005 to 2014. Our sample of workers is a balanced panel of all workers ever working in these firms.[18] Appendix Table A-1 provides descriptive statistics on our main sample of firms in 2008, prior to the start of the Great Recession. The average firm size in our sample is close to 9 employees, with an average of 38.7 weekly hours worked per employee. The average wage bill per employee is 20.6k euros. The Table also breaks down firms between eligible and non-eligible INPS codes. Despite being unequally distributed across industries, firms in eligible and non-eligible INPS codes are quite similar in terms of observable characteristics prior to the Great Recession. Firms in eligible INPS codes are slightly larger, but are quite comparable in terms of hours worked per employee, wage bill per employee, revenues, investment and liquidity. Table A-2 provides similar information for workers in our main sample of analysis. Workers in eligible INPS codes are more likely to be male and blue collars, and they are also slightly older than workers in non-eligible INPS codes, which reflect the fact that manufacturing is more represented in eligible INPS codes than in non-eligible INPS codes.

3 Effects of STW on Employment & Firm Outcomes

3.1 Identification

The eligibility requirements of the Italian CIGS create sharp variation in a firm's probability to use STW based on INPS codes and firm size.

Appendix Figure 2 provides direct evidence of this variation in access to CIGS by INPS codes and firm size. Panel A plots, among firms with eligible INPS codes in our sample, the evolution of the fraction of firms receiving CIGS in each calendar year t from 2005 to 2014, for firms with a maximum 6-month average size of 15 to 25 full time equivalent employees in year $t-1$ and for firms with a maximum 6-month average size of 5 to 15 full time equivalent employees in year $t-1$.

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those who are not eligible for CIGS (managers, apprentices and work-from-home employees) and those who are currently on unpaid leave (unless the firm has hired a replacement). Part-time workers are counted in full-time equivalent units. Eligible firms must have employed on average at least 15 employees in FTE in the 6 months prior to their application. Firms that have less than six months of activity should consider the average number of employees (in FTE) in the month or months of activity. In order to determine whether a firm meets the size requirement, we use the exact FTE firm size measure that determines CIGS eligibility as provided by INPS (the variable is called "forza aziendale").

[18]We restrict the main analysis to the period up to 2014, as an important reform of Italian labor market regulations started being implemented in 2015, which may have interfered with the effects of STW programs.

For firms with more than 15 FTE employees, CIGS take up rose sharply from less than 1% before the onset of the recession, to roughly 8% throughout the recession. While for firms with less than 15 employees, take up was essentially zero throughout the period. Panel B of Figure 2 replicates the same exercise for firms in non-eligible INPS codes. For both firms below and above the 15 FTE threshold, the take up is null throughout the entire period.

Our main identification strategy relies on using the interaction of being in an eligible INPS code, and having more than 15 FTE as a source of quasi-experimental variation in CIGS treatment after the onset of the recession in 2008. For each outcome Y, the baseline specification underlying our reduced-form graphical evidence is:

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\begin{aligned}
Y_{igst} = \quad & \sum_j \gamma_1^j \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[j = t] \right\} \\
& + \sum_j \sum_k \gamma_2^{jk} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s] \\
& + \sum_j \sum_k \gamma_3^{jk} \cdot \left\{ \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s] \\
& + \sum_j \sum_k \gamma_4^{jk} \cdot \left\{ \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s] + v_{igst}
\end{aligned}
\tag{1}
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where Y_{igst} denotes outcome Y for firm i, belonging to INPS code group g, in 5-digit industry s in year t. A firm can either be in the group of INPS codes eligible to receive CIGS ($g \in \mathcal{E}$) or in the group of non-eligible firms ($g \in \mathcal{E}^{\complement}$). $N_{i,t-1}$ is firm i's full time equivalent size in calendar year $t-1$. Note that by systematically controlling for 5-digit industry fixed effects and their interactions with time and firm size, we only exploit variation in eligibility of INPS codes across firms within the same fine-level industry codes. This variation stems from the interaction between industry codes and "codice autorizazzione".[19] To restrict our attention to comparable firms in a narrow neighborhood around the 15 FTE cut-off, we estimate the above model on our baseline balanced panel of firms who ever reach a size between 5 and 25 FTE. Our graphical evidence consists in plotting the estimated coefficients $\hat{\gamma}_1^t$ for all years t, which capture the evolution over time of the relative outcomes of firms that are just above and just below the 15 full-time equivalent employee threshold in eligible INPS codes, versus firms that are just above and below the same 15 full-time equivalent employee threshold in non-eligible INPS codes, but within the same 5-digit industry. The omitted year in specification (1) is 2007, so results are expressed relative to levels in year 2007.

Estimates of the effect of STW treatment are obtained from running IV models where we instrument the probability of STW treatment T by the triple interaction of being after the onset of the recession, being in an eligible INPS code and having more than 15 FTE employees:

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[19]This approach therefore fully controls for the fact that eligible firms are not evenly distributed across 5-digit industries nor across "codice autorizazzione".

$$Y_{igst} = \beta_{IV} \cdot T_{igst} \tag{2}$$

$$+ \sum_j \sum_k \eta_2^{jk} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s]$$

$$+ \sum_j \sum_k \eta_3^{jk} \cdot \left\{ \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s]$$

$$+ \sum_j \sum_k \eta_4^{jk} \cdot \left\{ \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s] + \mu_{igst}$$

$$T_{igst} = \kappa_1 \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[t > 2008] \right\} \tag{3}$$

$$+ \sum_j \sum_k \kappa_2^{jk} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[j = t] \right\} * \mathbb{1}[k = s]$$

$$+ \sum_j \sum_k \kappa_3^{jk} \cdot \left\{ \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s]$$

$$+ \sum_j \sum_k \kappa_4^{jk} \cdot \left\{ \mathbb{1}[j = t] \right\} \cdot \mathbb{1}[k = s] + \nu_{igst}$$

Note that our approach allows for fully flexible 5-digit industry specific time shocks, so that our identification is not confounded by differences in the way various industries responded to the recession. Furthermore, within industry, we allow for fully flexible INPS code time shocks. In other words, we allow for the fact that within industry, firms in eligible and non-eligible INPS codes might have fared differently during the recession. Finally, within industry, we also allow for fully flexible time shocks interacted with firm size. This controls for the fact that, in Italian Labor Laws, firms are exposed to different regimes when larger than 15 employees. Our strategy therefore allows for these differential regimes to impact differently over time, firms just below 15 employees and firms just above 15 employees, within each industry.

Given this rich set of flexible controls, our identification rests on the assumption that there are no unobservable time shocks that would be, within each industry, specific to firms that are in the set of INPS codes eligible to CIGS *and* whose size is just above the 15 FTE threshold. Or equivalently, we rely on the parallel trend assumption that size specific time shocks are common across eligible and non-eligible INPS codes within the same industry, and that "INPS code"-specific time shocks within a given industry are common across firm just above and below 15.

We explore the credibility and validity of these assumptions in a series of robustness tests in section 3.3. In terms of inference, we define two groups of firm sizes: a group with FTE above 15 in $t-1$ and a group with FTE below 15 in $t-1$, and we cluster all our standard errors at the INPS code times firm size group level. We explore additional inference approaches such as permutation tests (see footnote 24).

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3.2 Results

Figure 1 panel A starts by providing a graphical representation of the CIGS variation used to identify the causal effects of STW. It plots the coefficients $\widehat{\gamma_1^t}$ for all years t from a regression following specification (1), using as an outcome the probability that a firm receives CIGS treatment. It confirms the evidence from Appendix Figure 2 discussed above, that our instrument generates a sharp and significant first-stage. Our instrument accounts for a 5 percentage point increase in the probability of CIGS take-up by firms during the 2008 recession, starting from a baseline very close to zero for all firms prior to the onset of the crisis. Regarding the timing, the graph also shows that CIGS take-up quickly increased after the onset of the recession, and was high throughout the recession, with a peak in 2013.

Figure 2 displays estimates of the effect of STW on employment outcomes and wages. For each panel, we plot the coefficients $\widehat{\gamma_1^t}$ for all years from 2000 to 2014, based on a regression following specification (1), and we also report on the graph the estimated IV coefficient $\widehat{\beta_{IV}}$ of the effect of CIGS treatment following the IV model in specification (2).

First, the figure provides supporting evidence for our identifying assumption, by confirming, for each outcome, the absence of differential pre-trends between firms just below and just above the 15 FTE threshold in eligible and non-eligible INPS codes within the same industry.

The figure also suggests that STW has had large employment effects at both the intensive and extensive margin but insignificant effects on wage rates. Panel A shows that CIGS reaches its primary intent, by allowing firms to reduce employment at the intensive margin. Our estimates suggest that CIGS access enables firms to significantly reduce the number of hours worked per employee by $e^{-.51} - 1 = 40\%$ on average. While reducing employment at the intensive margin, CIGS treatment significantly increases employment at the extensive margin, as shown in Panel B. Firms experience a large and highly significant increase in headcount employment of $e^{.38} - 1 \approx 45\%$ due to CIGS treatment. Importantly, Panel C suggests that CIGS has no statistically significant effect on wage rates, defined here as earnings per hour worked per worker. This rigidity of wages means that the wage bill per employee decreases significantly with CIGS, by about 45% as shown in panel D, since workers work less hours for the same wage rate cost to the firm.

In Table 1, we provide additional results of the effects of STW treatment on various firms' outcomes. Panel B shows that the positive employment effects are driven by an increase in the relative number of employees in open-ended contracts. The estimated IV coefficient for the effect of CIGS treatment on the log number (headcount) of employees in open-ended contract is $\beta_{IV} = .61 \ (.043)$, but the number of employees in fixed-term contracts is negatively impacted by CIGS treatment ($\beta_{IV} = -.40 \ (.11)$). This reallocation of employment between open-ended and fixed-term contracts reflects the duality of the Italian labor market (Boeri [2011]).

Panel C of Table 1 presents results on the effect of STW on balance-sheet and productivity outcomes. These results are estimated on the sample of firms that were matched to their balance sheet data from CERVED. To get a better idea of the magnitude of the effects, for all outcomes in panel C, we report the estimated IV coefficient β_{IV} scaled by the average value of the outcome for

non-eligible firms in the post 2008 period. Our results suggest that there is no significant effect of STW on firms' total output. We measure total output by firm value added, that is, total revenues plus unsold stocks minus cost of goods and services used in production.[20] We find a small positive but insignificant effect of STW of .09 (.16). Because total output is not significantly affected, but workers work less hours when treated with STW, valued added per worker goes down significantly by roughly 50% (12%). When looking at labor productivity as a whole, defined as firm value-added divided by total number of hours worked (instead of value added per worker), we find a smaller negative effect of STW, of -.14 (.10). These results suggest that firms reallocate labor between intensive and extensive margins, with limited overall effect on labor productivity defined as output per hour worked. We also explore the effect of STW on total factor productivity (TFP) and find a small negative but insignificant treatment effect of STW on firms' TFP. [21] Interestingly, these results provide evidence that the employment responses to STW are real responses, and are not simply driven by reporting behavior. One may indeed worry that collusive avoidance behavior may occur within the firm, by which firms report less hours to INPS so that workers may benefit from the STW subsidy, while real working hours remain unchanged. If it were the case though, revenues and value-added measured in CERVED would not be affected, and measures of the firm's labor productivity, and TFP would go up significantly in response to STW. The lack of significant effect of STW on productivity indicates that our estimated employment responses to STW are driven by real behavior rather than avoidance.

Finally we investigate the effect of STW on firm's liquidity, defined as cash and cash equivalents, and find a positive effect (although very imprecisely estimated). Combined with the large employment effect of STW and with wage rigidity, the fact that a firm's liquidity reacts to STW treatment, suggests that internal funds constraints may play a role in amplifying employment responses to negative productivity shocks, as suggested by Schoefer [2015].[22]

3.3 Robustness

The first potential concern with our identification strategy is that firms may endogenously select into either firm size or eligible INPS code in order to benefit from STW.

In terms of firm size, treatment eligibility is determined by a firm's largest 6-month continuous FTE size in the year prior to STW application. While this may limit manipulation opportunities in practice, firms with private information about future shocks may still have the possibility to endogenously adjust their FTE size ex-ante. To assess to what extent size manipulation creates significant selection susceptible of biasing our results, we first display in Appendix Figure A-2 the probability density function of FTE size over our entire sample period. Size manipulation to

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[20]In effect, this is equivalent to defining firm output as total profits plus total capital depreciation plus total wage cost.

[21]We follow Calligaris et al. [2016] and define TFP, as $TFP = VA/(L^{\alpha}K^{\beta})$ where VA is total value added, L is total wage bill, K is fixed capital net of depreciation. We estimate $\alpha = \mathbf{E}[L/VA]$ at the 2-digit industry level and assume constant returns to scale (i.e. $\beta = 1 - \alpha$).

[22]We provide additional evidence on the role of liquidity constraints in section 5.1.

benefit from STW treatment in response to the 15 FTE threshold should result in "bunching from below", with missing mass just below the threshold, and excess mass above. The figure displays little signs of bunching from below. To provide more formal testing for size manipulation, we report in Appendix Figure A-3 results from McCrary tests of the presence of a discontinuity in the probability density function (pdf) of FTE size. We report the statistic from the test and its confidence interval for each year, and separately for eligible and non eligible INPS codes. In the presence of manipulation, we would expect the presence of a significant discontinuity in the pdf for eligible INPS codes, that would be more pronounced during the Recession, if access to STW is indeed valuable during Recession. The figure shows that, for both eligible and non eligible INPS codes, no statistically significant discontinuity in the pdf of FTE can be found, and that this holds for each year from 2000 to 2014. As a final exercize to assess the robustness of our results to size manipulation, we run a "doughnut" regression, where we exclude all firms with FTE between 12 and 18. Results, displayed in Table 2 column (1) are almost identical to our baseline results, confirming that our estimated effects are not driven by selection due to size manipulation by firms.

Beyond their FTE size, firms may be willing to manipulate their INPS code, either through their codice autorizzazione or their industry code, in order to gain eligibility to STW. In practice, while not impossible, such manipulation is complicated, and extremely rare. Appendix Figure A-4 shows that less than .6% of firms change eligibility status due to a change in their INPS code every year in our sample, with the same fraction ($\approx$ .3%) of firms moving from being eligible to non eligible and moving from being non eligible to being eligible. Furthermore, these fractions are extremely stable over time. These results suggest that it is highly unlikely that firms endogenously self-select into INPS codes in order to get access to CIGS.

The identifying assumption underlying our strategy is that there is no time shock that would be specific to firms just above 15 FTE *and* eligible INPS codes within 5-digit industry codes. To assess the credibility of this assumption and the robustness of our approach, we proceed in several steps.

First, we show that there is little evidence of significant differential time shocks between eligible and non eligible INPS codes within the same industry for firms just below 15 FTE. To this effect, we directly estimate differential trends across INPS codes within 5-digit industry codes using only firms with FTE below 15 and therefore non eligible to receive STW. We estimate a model of the following form on a sample restricted to firms between 5 and 15 FTE in year $t-1$.

$$Y_{igst} = \alpha_1 \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[t \geq 2009] \right\} + \sum_k \alpha_2^k \cdot \mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[k = s] + \sum_j \sum_k \alpha_3^{jk} \cdot \mathbb{1}[j = t] \cdot \mathbb{1}[k = s] + v_{igst} \quad (4)$$

We report in column (2) of Table 2, the estimated coefficient α_1 of the interaction for being in eligible INPS codes after the start of the Great Recession. Results for all outcomes of interest show that differential effects of the Great Recession for eligible vs non eligible INPS codes within the same industry are either not statistically significant or of very limited magnitude for firms below 15

FTE. These results confirm that within 5-digit industry, variation in CIGS eligibility across INPS codes, which is mostly a product of regulations from the Ministry of Labor in the 1970s, is quite plausibly exogenous to economic conditions today.[23]

The previous evidence suggests that, for firms below 15 FTE, there is no evidence of time shocks that would be, within 5-digit industries, specific to eligible INPS codes. But of course finding no differential trends across eligible and non-eligible INPS codes for firms below 15 employees does not preclude the possibility that such differential trends exist for firms above 15 employees. Indeed, firms below and above the 15 FTE differ in terms of the dismissal regulations they are subject to. Heterogeneity in the treatment effects of employment regulation across INPS codes may then create differential trends across INPS codes for firms above 15 employees. We assess the robustness of our results to this potential threat in two simple ways.

First we can directly assess the extent of heterogeneity in the treatment effects of employment regulation across INPS codes by running placebo specifications across non-eligible INPS codes. We restrict the sample to non eligible INPS codes only. Among these non eligible INPS codes, we randomly select a series of INPS codes, to which we attribute a placebo "eligible" status and then run the reduced-form of our baseline IV specification (3). We replicate this procedure 100 times and obtain bootstrapped estimates of the placebo reduced-form coefficient for the triple interaction of being a firm above the 15 FTE threshold in (placebo) eligible INPS codes after 2008. We report the mean and standard error of the distribution of these 100 bootstrapped estimates in column (4) of Table 2. All estimates are statistically insignificant, very close to zero, with tight standard errors, showing no evidence for heterogenous responses to the recession across INPS codes by firms just above 15 FTE. This evidence clearly alleviates the concern that our baseline estimates may just be picking up some idiosyncratic time shocks at the INPS code level for firms above 15 FTE during the Great Recession.[24]

Second, we use the fact that for some firms, the size thresholds that determine CIGS eligibility and employment dismissal regulation do not coincide. One reason for the two thresholds not to coincide is that employment legislation regulating dismissals apply in Italy when a firm reaches 15 employees within a single establishment, *or 60 employees in the firm in Italy as a whole*. But, as explained in footnote 15 above, eligibility to CIGS, and therefore eligibility requirements, all apply

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[23]As a consequence, this means that our baseline results do not rely much on correcting for differential trends across eligible and non eligible INPS codes within industry, using firms with less than 15 FTE. This can be clearly seen from results in column (3) of Table 2 which reports estimates from a specification where we focus on firms between 15 and 25 FTE only, and therefore only identify the effects of STW by comparing firms in eligible vs non eligible INPS codes, before vs after the onset of the Great Recession. Results are indeed extremely similar to our baseline results.

[24]This placebo procedure naturally lends itself to a simple permutation test for the estimates obtained from our baseline specification. In other words, we can use the bootstrapped placebo estimates to determine what the likelihood would be of getting our baseline estimates if "treated" INPS codes were actually allocated randomly. We report in Appendix Figure A-6 the p-value from such tests for the baseline estimate of each coefficient $\hat{\gamma}_1^t$ in specification 1, each panel corresponding to a different firm outcome. Results show that for the outcomes (intensive and extensive employment margin, wage bill, etc) where we find large statistically significant effects in our baseline specification, the probability of finding such effects "at random" is extremely small, and always below 5%. To the contrary, for the wage rate, where we find no statistically significant effect in our baseline specification, the p-value is large, which further suggests that wage rates seem to be totally unresponsive to STW.

at the establishment level. In Table 2, we use a sample of multi-establishment firms that have more than 60 employees across Italy, and compare their establishments that are around the 15 FTE, by running on this sample our baseline IV specification (2). Because all these establishments are already subject to dismissal regulation, the identifying variation in CIGS eligibility cannot be confounded by potential heterogeneity in the treatment effect of employment protection laws. Results reported in column (5) of Table 2 are qualitatively similar to our baseline estimates, with large negative effects on employment at the intensive margin and large positive effects on employment at the extensive margin, although much less precise due to the small size of this sample. In column (6) of Table 2, we provide additional evidence of the robustness of our results by focusing on another small group of firms in the retail sector for which the size thresholds that determine CIGS eligibility is set at 50 FTE, and therefore does not coincide with the 15 FTE size threshold for employment dismissal regulation. We create a sample of single-establishment firms in the wholesale and retail sectors that ever reach a maximum 6-month FTE size between 25 and 75. We estimate our baseline model specification (2), on this sample, simply replacing the dummy variable $\mathbb{1}[N_{i,t-1} > 15]$ by a dummy for reaching a maximum 6-month firm size above 50 FTE in year $t - 1$. Results reported in column (6) are again very comparable to our baseline estimates, with negative effects on hours and large positive effects on headcount employment. Although point estimates are similar to our baseline estimates, standard errors are much larger due to the small size of this sample.

Taken together, this set of results provides evidence of the credibility of our identifying assumption, and of the robustness of our baseline results.

3.4 Dynamic Effects

As explained in section 2, CIGS treatment is temporary. Firms can receive STW for a maximum of 12 months over a fixed 5-year period and, in practice, both average and median duration are very close to 52 weeks. Furthermore, INPS codes and firm size, which determine access to STW, are persistent over time. As a result, a firm that is eligible based on firm size and INPS code in year t is not only more likely to receive treatment in t, but also more likely to have received treatment in $t-1$, $t-2$, etc. Appendix Figure B-1 provides direct evidence of the correlation between current eligibility and past treatment by plotting the effect of the triple interaction $\mathbb{1}[g \in \mathcal{E}] * \mathbb{1}[N_{i,t-1} > 15] * \mathbb{1}[j = t]$ on the probability to have been receiving treatment in the past 5 years.

Our baseline estimates $\widehat{\beta_{IV}}$, which use the triple interaction $\mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[N_{i,t-1} > 15] \cdot \mathbb{1}[t > 2008]$ as an instrument, are therefore identifying the total effect of exposure to STW during the Great Recession. In other words, they capture both contemporaneous effects of STW treatment and past dynamic effects of STW treatment. One may however be interested in unpacking this sequence of dynamic effects to gain further insights on the impact of STW on firms' and workers' outcomes.

To identify the the sequence of dynamic treatment effects of STW $\{\beta_0^{TOT}, \beta_1^{TOT}, ..., \beta_k^{TOT}\}$, we develop a methodology similar in spirit to the recursive identification of dynamic treatment effects in Cellini, Ferreira and Rothstein [2010]. All the details of the procedure are given in Appendix B.2. The main intuition is straightforward. Take all firms that are active in 2009, and define our

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instrument for STW access in 2009 Z_{2009} as the interaction between firm size and INPS code in 2009. The difference in outcome in 2009 of eligible firms in 2009 ($Z_{2009} = 1$) versus non-eligible firms ($Z_{2009} = 0$) only reflects the contemporaneous effect of treatment (β_0^{TOT}) in 2009. This is because there is no difference in 2009 in the probability of past treatment between eligible and non-eligible firms in 2009 as clearly shown in Appendix Figure B-1. Because eligible firms in 2009 are not only more likely to be treated in 2009, but also to be treated in 2010, the difference in their outcome in 2010 will reflect both the 1-year lagged effect of treatment in 2009 (β_1^{TOT}) and the contemporaneous effect of treatment (β_0^{TOT}) in 2010. And so on and so forth. That is, the difference in outcome in any year $k \geq 2009$ between firms that are eligible versus non eligible in 2009 capture the dynamic Intention-To-Treat (ITT) effect from treatment in 2009 after k years, allowing for potential future treatment.

Exploiting this intuition, we show in Appendix B.2 that the sequence of ITT effects are identified by the coefficients for each year ($\beta_{2009}^{RF}, \beta_{2010}^{RF}$, etc.) of the reduced form relationship between the outcome and Z_{2009}. We also show that ITT effects have the following recursive structure as a function of TOT effects:

$$ITT_0 = \hat{\beta}_{2009}^{RF} \quad = \quad \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}} \tag{5}$$

$$ITT_1 = \hat{\beta}_{2010}^{RF} \quad = \quad \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2010}}{\mathrm{d}Z_{2009}} + \beta_1^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}}, \qquad etc. \tag{6}$$

Using estimates of $\hat{\beta}_{2009}^{RF}, \hat{\beta}_{2010}^{RF}$, etc., and of the first stages $\widehat{\frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}}}, \widehat{\frac{\mathrm{d}T_{2010}}{\mathrm{d}Z_{2009}}}, etc.$, we can identify the sequence of dynamic TOT effects $\{\hat{\beta}_0^{TOT}, \hat{\beta}_1^{TOT}, ..., \hat{\beta}_4^{TOT}\}$.

Figure 3 reports the dynamic effects of STW treatment on hours per employee. Results suggest that the entire employment effects of STW are on impact. At the time of treatment, log hours per employee decrease by .3, but this effect disappears immediately after treatment, with no significant long term impact. Appendix Figure B-2 shows similar patterns for other employment outcomes. Upon treatment, log headcount employment increases by .2, the log wage bill decreases by .2, log open-ended contract increase by .4, but all these effects dissipate instantly as treatment disappears. In the long run, the recursive identification lacks precision, as it makes standard errors become somewhat large.[25] Yet point estimates are consistently small, and close to zero, indicating no significant long term effects of treatment. This dynamic pattern of results, with short run employment effects that quickly dissipate after treatment, is confirmed by our analysis of the dynamics of outcomes at the worker level, which we now turn to.

4   Dynamic Effects & Insurance Value of STW for Workers

The analysis so far has focused on firms, and firms' outcomes. Yet, understanding how STW policies interact with workers' employment and earnings dynamics is equally key to assess the

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[25]We report bootstrapped standard errors for the TOT effects. Because of the recursive nature of identification, standard errors using the Delta-method equally suffer from this lack of precision.

welfare consequences of such programs.

In this section, we explore two important dimensions of the relationship between workers' labor market dynamics and STW. First, we document how the outcomes of workers on STW compare to the outcomes of other workers, and to the outcomes of the same workers prior and after being on STW. The difference in outcomes informs us about the difference in marginal utility of consumption of individuals receiving vs contributing to the STW policy, which, in the spirit of the optimal tax and social insurance literature, is "sufficient" to evaluate the marginal welfare value of the transfer operated by the policy (Chetty [2006]).

Second, we are also interested in identifying the causal effect of receiving STW treatment on the dynamics of workers' labor market outcomes. One important rationale for STW programs is that job separations may actually destroy positive surplus created in employment relationships and can have significant short run as well as long term negative consequences for workers (Yagan [2017]). Many different mechanisms may participate in creating these negative effects of separations, from various labor market frictions, to specific human capital accumulation, experience effects or other scarring/discrimination effects. A prevalent idea in the public debate is that STW, by reducing the incidence of separations, may therefore have beneficial dynamic "insurance" value to workers by preserving the surplus created by the employment relationship. By estimating the causal effect of STW on the dynamics of workers' outcomes, one can directly assess the validity of these claims.

4.1   Event Studies

We start by documenting, using event studies, the dynamics of workers' outcomes around STW treatment. We create a panel of the labor market histories of all employees of firms active and with FTE firm size $\in (5; 25]$ at any point between 2000 and 2015. An event year is defined as the first year a firm experiences a STW spell. Treated individuals are individuals who are employed in the firm at the start of the first STW spell. We run event study regressions on this sample of treated individuals, controlling for individual and calendar year fixed effects and report in Figure 4 estimates for three outcomes, the probability of being employed, the total number of hours worked per year (unconditional on employment), and total earnings plus all social transfers including STW. All estimates are relative to event year -1, and scaled by the average level of the outcome among the treated in year -1. In Figure 4, we also report results for two comparison groups of similar workers not treated by STW. The first comparison group consists of workers with similar characteristics as treated workers pre-treatment, but who cannot access STW as they work in firms non-eligible to CIGS based on FTE size and eligibility. To create this group, we match each treated worker, using Mahalanobis nearest-neighbour matching without replacement, with a worker from the sample of non-eligible firms with FTE size $\in (5; 25]$ in event year -1. Matching is based on gender, age, job characteristics at event time *t-1*, employment status, annual weeks worked, earnings and firm size at *t-1*, *t-2*, *t-3* and *t-4*, and main industry at *t-1*. The second comparison group consists of workers in non-eligible firms in event year -1 who experience a mass layoff in event time 0, and is created following a similar nearest-neighbor-matching strategy using the same variables.

Results of the event study estimates for all three groups and all three outcomes are reported in Figure 4 and reveal interesting dynamic patterns. First, there seems to be no differential trends pre-event across the treated workers and our comparison groups, signalling little anticipation of STW treatment in terms of labor market trajectories. Second, treated STW workers experience, on impact, a sharp reduction of roughly 30% of their worked hours, a reduction very close to our IV estimate of the effects of STW on hours using firm outcomes. This sharp drop in hours translates into a milder drop of 18% in total earnings and transfers, because of the high replacement of the STW subsidy.

When comparing the labor market outcomes of treated workers to our comparison groups during the treatment period, it is interesting to note that workers experiencing STW treatment maintain a probability of being employed similar to workers in non-eligible firms, and much larger than workers in the layoff comparison group. This is indicative that STW has indeed a positive effect on employment in the short run, as shown in the previous section. But despite having a similar probability of being employed, treated workers experience a reduction in hours that make their total employment, measured by total annual hours worked, much lower (≈ 25 percentage point) than workers in non-eligible firms, and only 10 to 15 percentage point larger than laid-off workers. But the high replacement rate of STW makes their total income from earnings and transfers significantly larger ($\approx 18\%$) than laid-off workers.

Labor market dynamics after treatment are also informative. After treatment is over, treated workers experience a sharp drop in labor market outcomes, confirming the reversal also observed for firms' outcomes. First, there is a sharp drop in the probability of employment and in total hours worked in the next two years following treatment.[26] There is also a significant drop in total earnings and transfers of treated workers, which, 2 years after treatment, only represent 60% of their pre-treatment level. In comparison to non-eligible workers, treated workers fare much worse in terms of all labor market outcomes in the medium and long run. But even more strikingly, two to three years after treatment, labor market outcomes of treated workers are no longer significantly different from those of non-eligible workers who were laid-off at time 0. This suggests that, while STW offers some short run insurance, in the medium run, being laid-off or being put on STW are somewhat equivalent in terms of labor market outcomes.

4.2 Identifying Causal Dynamic Effects on Workers

We want to understand to what extent the interesting dynamic patterns from the previous event studies reveal the deeper causal dynamic impact of STW treatment. Endogeneity concerns prevent interpreting the event study estimates on the treated as the causal dynamic impact of short time work. The incidence and timing of CIGS treatment across firms are indeed not random and workers within these firms may differ from other workers along various characteristics affecting their labor

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[26]The decrease in total hours worked between event year 0 and 1 is a little less severe (15 percentage point) than that of the probability of employment (around 20 percentage point), and reflects the fact that hours conditional on employment increase post treatment, a result similar to what was observed in firm level outcomes.

market dynamics. Two things can be done to tackle this issue. First, we can use event studies estimates from our comparison groups to get bounds on counterfactuals, and therefore obtain bounds on the dynamic treatment effects of STW. Second, we can also get a causal estimate of the dynamic effect of STW on workers by implementing a version of our IV recursive identification method used in section 3.4, but focusing on workers outcomes instead of firms. All the details and results of these two approaches are given in Appendix B.2.

Results, displayed in Appendix Figure B-3, confirm that STW has a positive effect on workers outcomes during treatment and therefore provides short term insurance to workers in firms exposed to shocks. Yet, these effects entirely disappear after treatment so that STW provides no longer term insurance to workers. In other words, there was no long term beneficial effect of keeping treated workers in firms treated by CIGS during the Great Recession in Italy. This also suggests that there is limited scope for experience effects in the CIGS context, which confirms a stream of evidence on the absence of significant returns to experience for workers treated by active labor market programs (Card and Hyslop [2005]). To understand why STW provides no long term insurance to workers, the next section investigates patterns of selection of firms into STW treatment, and its implications for reallocation of workers in the labor market.

5 Selection & Reallocation effects

5.1 Selection into STW

Can the selection of firms into STW take-up explain the limited insurance value of STW treatment for workers? To answer this, we analyze selection patterns and heterogeneity in treatment effects along two important dimensions: firms' productivity levels pre-recession, and firms' likelihood of mass separations during the recession.

We start by ranking firms in quartiles of the distribution of their average yearly productivity over the 2007-2008 period. We use two different measures: labor productivity, defined as firm value-added divided by total number of hours worked in the firm, and TFP, defined as in section 3.2 above. We then run the first-stage regression (3) separately for firms in each quartile of the distribution to investigate how pre-recession productivity levels differentially affect take-up of STW. Results of the estimated coefficients $\hat{\kappa}_1$, reported in Figure 5 panel A, indicate that firms that had very low productivity prior to the recession are significantly more likely to take up STW conditional on eligibility. Firms in the bottom quartile of pre-recession TFP are almost 7 percentage point more likely to take-up STW than firms in the top quartile, conditional on eligibility. Do these firms benefit more from access to STW? In panel B and C of Figure 5 we report estimates of $\hat{\beta}_{IV}$, from the 2SLS-IV model (??), again estimated separately for each quartile of the pre-recession productivity distribution. Panel B shows that low productivity firms tend to reduce hours more in response to STW treatment, but panel C shows that this comes with limited total effects on employment. To the contrary, firms that were experiencing high productivity levels pre-recession seem to exhibit a much larger positive treatment effect of STW treatment on employment.

Turning to the targeting efficiency of STW, we also investigate whether firms that have a higher likelihood to separate workers are more likely to take-up STW. To investigate this effect, we start by building a prediction model of the probability of mass layoff during the recession using a rich set of regressors including balance-sheet information and Bartik-style instruments.[27] We estimate this model using LASSO on the sample of non-eligible firms with more than 15 FTE. We then use the model to predict the incidence of mass layoff during the recession among eligible firms, and rank firms in quartiles of the distribution of the prediction score. Finally, we replicate the selection and heterogeneity analysis of Figure 5 across firms in the different quartiles of the mass layoff score. Results in panel A of Figure 5 show that firms that would have been highly likely to layoff workers in the absence of STW are 80% more likely to select into treatment, conditional on eligibility. Interestingly, low risk firms still do take up significantly. Panel B indicates that firms with higher mass layoff risk scores reduce hours more when treated by STW but panel C shows no significant heterogeneity in treatment effects on employment.

Overall, results of Figure 5 contribute to explaining the dynamic patterns of the treatment effects of STW observed for firms and workers. Firms taking up STW exhibit low productivity to begin with, and are likely to layoff workers in a downturn. When the aggregate shock to the economy is quite persistent, as was the case during he Great Recession in Italy, STW can only be a short term fix, which explains why the positive employment gains of STW immediately disappear after treatment. The results suggest that STW may be more effective at preserving employment in high productivity firms experiencing temporary shocks. But in practice, STW subsidizes mostly firms that have permanently lower levels of productivity, with more limited effects on employment.

5.2 Reallocation effects

It is often argued that labor market programs hinder the "cleansing" effect of recessions. By keeping workers in low productivity firms, which are much more likely to take up the program, STW is indeed susceptible of affecting the reallocation of workers towards more productive employment relationships. To investigate such claims, we leverage the rich spatial variation available in Italy across more than 600 local labor markets (LLM) defined by the Italian statistical agency (ISTAT) and estimate how an increase in the fraction of workers treated by STW in a LLM affects employment outcomes of non-treated firms.[28] In each LLM, we define the fraction of treated workers as the total numbers of workers on STW divided by the total number of employed workers observed from INPS records.[29] Appendix Figure C-1 shows the large amount of variation in the intensity of

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[27] A mass layoff is a layoff of at least 5 workers over a time period of 120 days. We define an indicator for mass layoff taking value 1 in each year in which we observe at least 5 layoffs occurring over a 4-month period. The regressors included in the prediction model are: a Bartik-style index for employment shocks at the 2-digit industry level and provincial level, labor productivity, a Whited-Wu index of credit constraints, net revenues per employee, profits per employee, liquidity over total assets, cash flows over total assets, tangible and intangible assets over total assets. All regressors enter the model in levels, one-year lags and first differences.

[28] We use the ISTAT 2011 classification of municipalities into 611 local labor markets.

[29] For employed workers, we use information about the address of the place of work available in the INPS individual records.

STW treatment across LLM during the recession. Importantly, this spatial variation arises mostly within rather than between Italian regions. Yet, variation in the intensity of STW treatment across LLM will be of course endogenous to local economic and labor market conditions during the Great Recession, which might affect employment outcomes of non-treated firms. To account for this threat, we instrument the fraction of workers treated by STW during the recession by the average yearly fraction of eligible workers in the LLM based on the interaction between firm size and INPS codes in the pre-recession period, in the years 2005 to 2008. We identify the reallocation effects of STW on non-treated firms at the LLM level based on the following model:

$$\underset{t,t'}{\Delta} Y_{ij} \;=\; \alpha + \beta_{IV}^R \underset{t,t'}{\Delta} T_j + X_j' \gamma_0 + W_i' \gamma_1 + \varepsilon_{ij} \tag{7}$$

The model is estimated on the sample of all firms i that are non-eligible to STW based on their characteristics in 2008. $\underset{t,t'}{\Delta} Y_{ij}$ are long differences in average yearly employment outcomes of firm i in LLM j between the recession period t' and the pre-recession period t.[30] $\underset{t,t'}{\Delta} T_j$ is the long difference in the average yearly fraction of workers treated by STW in LLM j between period t and t'. The long difference in the fraction of workers treated by STW in LLM j is instrumented by the average yearly fraction Z_j of workers of LLM j that are eligible to STW during the pre-recession period based on the interaction between their firm size and INPS code in the pre-recession period. We control for a rich vector W_i of firm characteristics, correlated with CIGS take-up, and likely to affect firm employment outcomes during the recession. The vector is composed of 5-digit industry fixed effects and codice autorizzazione fixed-effects, as well as bins of firm size in 2008. We also control for LLM characteristics that could be correlated with the fraction of treated workers and likely to affect employment outcomes during the recession, such as the industry and firm size composition of the LLM and the initial unemployment rate in the LLM prior to the recession. Identification therefore comes from comparing LLM with similar characteristics, including firm size composition and industry composition, but with different allocations of workers within firm size times INPS codes bins during the pre-recession period. We propose various tests for the validity of our exclusion restriction below. Standard errors are clustered at the LLM level. Appendix Figure C-2 provides evidence of the strong first-stage relationship between the fraction of eligible workers in a LLM during the pre-recession years 2005-2008 and the fraction of workers on STW during the recession conditional on controls for firm and LLM characteristics.

Panel A of Figure 6 provides striking evidence of the presence of significant reallocation effects of STW within LLMs. The graph is a bin-scatter plot of the reduced-form of the IV model (7), that is, the relationship between the instrument Z (the fraction of eligible workers in the pre-recession period in a LLM based on the interaction of firm size and INPS codes) and the long difference in log employment of non-eligible firms. The reduced-form relationship is strongly negative, indicating

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[30]In our baseline estimation of model (7), we compare the recession years 2010-2013 to the pre-recession years 2005 to 2008. Results are robust to the precise definition of the pre and post recession periods.

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that in LLMs with a larger fraction of eligible workers in the pre-recession period, employment growth of non-eligible firms was significantly worse during the recession. The corresponding IV estimate is $\beta_{IV}^{R}=-.94$ (.22), which means that a 1 percentage point increase in the fraction of treated workers in a LLM reduces employment of non-eligible firms by .94%. Another way of assessing the magnitude of these spillover effects on non-treated firms is to ask the following question: what is the impact of preserving one employment relationship in a firm treated by STW on the number of jobs in non-treated firms. Given our estimates of the effect of STW treatment on employment of treated firms, our β_{IV}^{R} estimates imply that for one job "saved" by STW in a treated firm, employment in non-treated firms decreases by .03 job. Table 3 summarizes the results, and also shows that the employment effects are driven by a significant decline in inflows in non-eligible firms (measured as the number of new hires) as the fraction of workers treated by STW increases in the LLM.

By keeping more workers in low productivity firms, and by reducing the number of workers real-locating to non-treated firms, which have higher productivity than treated firms on average, STW is likely to affect overall productivity within the LLM. We explore this possibility by computing LLM level measures of TFP and running IV model similar to (7) with LLM TFP long differences as an outcome.[31] The IV results, displayed in Table 3, confirm that STW has a significant negative impact on overall TFP within LLM, with a one percentage increase in the fraction of workers treated by STW translating into a roughly 2% decrease in TFP.

One may worry about the validity of the exclusion restriction underpinning the IV estimates. This restriction may be violated if the fraction of workers eligible to CIGS in the pre-recession period based on the interaction of firm size and INPS code is correlated with other unobserved characteristics of the LLM affecting employment and TFP growth. To assess the credibility of our strategy we run placebo models similar to (7) where we now compare long differences between 2000-2005 and 2005-2008, and use as a placebo instrument the fraction of eligible workers in the LLM based on the interaction between firm size and INPS codes in the 2000-2005 period. Because there is no take-up of CIGS during the 2005-2008 period, there is no first stage in this model, so that our placebo instrument will only pick up an effect if the exclusion restriction does not hold, and the instrument is correlated with other determinants of employment and TFP growth within a LLM. The reduced-form relationship of the placebo model for employment growth of non-eligible firms in the LLM are reported in panel B Figure 6. We clearly see no significant relationship between the placebo instrument and the outcomes, which provides comforting evidence for the validity of our exclusion restriction. We report similar placebo models for TFP growth in Table 3 and find no significant relationship between our instrument and TFP growth in the LLM in the pre-recession period.

Overall, by leveraging the rich spatial variation across LLM in Italy, and the variation in STW treatment created by the interaction of firm size and INPS codes, these results provide compelling evidence that STW has significant equilibrium effects within labor markets. STW creates significant

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[31] We define, as before TFP as TFP = VA/($L^{\alpha}K^{\beta}$), but we now aggregate all variables (VA, L and K) at the LLM level.

spillover effects on non-treated firms through reallocation of workers. Non-treated firms are less able to grow and hire new workers as a result. And by tilting the allocation of workers towards less productive firms, STW has a significant negative impact on TFP growth in the labor market.

6 Welfare Implications for STW Programs

To understand the welfare implications of our empirical results, this section develops a simple search and matching framework of labor market equilbrium, allowing for labor adjustments both at the intensive and extensive margin. The model serves three important purposes. First, it offers a general tractable model in which one can rationalize the empirical evidence of sections (3) to (5). In particular, we clarify the conditions under which general search and matching models can generate the observed employment responses to STW treatment. Second, we derive a general formula for the optimal subsidy rate of STW policies and clarify the welfare trade-offs inherent to STW policies. Finally, we calibrate a version of the model based on our reduced-form evidence to provide estimates of the welfare effects of STW and conduct counterfactual policy analysis.

6.1 A General Model With Intensive & Extensive Labor Adjustments

We consider a unit mass of risk averse workers in a frictional labor market where firms are exposed to both idiosyncratic and aggregate productivity shocks. For simplicity, we assume that for each level of the aggregate shock, there are two levels of idiosyncratic productivity (high ϵ_H and low ϵ_L) and we denote by ρ the (endogenous) fraction of high productivity employment in stationary equilibrium.

In each period t, u_t unemployed workers meet firms with a vacancy at a rate described by a constant returns to scale matching technology function $M(u_t, v_t)$, increasing and concave in both arguments. We define labor market tightness $\theta_t \equiv \frac{v_t}{u_t}$ as the ratio of vacancies to unemployment, which is, given M, a suff icient statistics for both the vacancy filling probability $q(\theta_t)$ and the job finding probability $\phi(\theta)$. Each period, a fraction δ of existing employment relationships is destroyed exogenously.

We assume random matching between workers and firms irrespective of their productivity, that is, search is not directed across separate search markets for high and low productivity firms. While some papers have explored STW in the context of directed search models, there are a few important reasons why sticking to the more general case of random matching might be preferable.[32] First, random matching proves critical in generating transparently the spillover effects that we observe in the data. Second, a key feature of directed search models is that equilibrium employment will be socially efficient absent STW. Consequently, there is no room for correcting potentially inefficient employment levels over the business cycle, which makes one of the main argument in favor of the existence of STW irrelevant. Finally, a corollary is that in directed search models, ex-ante utility is always equalized across workers searching for high and low productivity employment contracts.

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[32]See Cahuc, Kramarz and Nevoux [2018] for a static version of a directed search model with STW.

Which means that STW transfers towards low productivity employment contracts have no insurance value. This is because the ability to direct search across search markets for low or high productivity employment contracts already provides insurance for workers against firms' idiosyncratic shocks. With random matching, workers cannot insure themselves against the risk of being matched with a low productivity firm, which provides an additional insurance argument in favor of STW subsidies.

Workers Workers are identical. They value consumption and have disutility in hours worked, according to a general utility function $u(c, h)$, $u'_c > 0$, $u'_h < 0$. Workers are risk-averse in consumption, $u''_c < 0$ and discount the future at rate β. There is no storage technology, agents consume all they earn every period. Workers therefore value insurance against income fluctuations provided by the government, which takes two forms. First, unemployment insurance benefits b (extensive margin insurance) are given to unemployed workers. Second, intensive margin insurance is provided in the form of a STW subsidy of rate τ given against earnings losses for hours reductions below a threshold level $\bar{h}$ for workers in low productivity firms. The total amount of STW benefits for a worker in the program is therefore $b^{STW} = \tau w(\bar{h} - h)$. Both UI and STW benefits are funded by a lump sum tax t levied on all workers.

The value function of a worker when unemployed, W^u is:

$$W^u = u(b, 0) + \beta(\phi W^e + (1 - \phi)W^u) \tag{8}$$

The value function of a worker when employed by firm of productivity $\epsilon_k \in \{\epsilon_H, \epsilon_L\}$, is W_k^e

$$W_k^e = u(c_k, h_k) + \beta(\delta W^u + (1 - \delta)W_k^e) \tag{9}$$

Workers can endogenously quit their job every period. They will choose not to do so whenever the employment relationship entails a positive surplus, which means that the continuation value of being employed in a firm of productivity ϵ_k is at least equal to the value of being unemployed $W_k^e - W^u \geq 0$. The zero surplus condition $W_k^e - W^u = 0$ implicitly defines the reservation values of wage and hours that a worker is willing to accept for any employment relationship. Note that these reservations values will be functions of the UI benefits and STW subsidy. In particular, the lower bound on hours that workers are willing to accept decreases with STW, *ceteris paribus*. In other words, STW relaxes the constraint on offering lower hours contracts.

Firms Firms produce an homogenous consumption good using labor inputs according to the technology $\epsilon_t F(h_t, n_t)$. We keep the production function general and allow the marginal product of labor to potentially differ at the intensive (hours worked per employee h) vs extensive margin (number of employees n). This captures the simple fact that the return to adjusting labor may differ when increasing hours per employee or when hiring a new employee.

Firms determine every period the number of vacancies to be posted v_t to maximize profits:

$$\Pi(\epsilon_t, n_{t-1}) = \max_{v_t}\{\epsilon_t F(h_t, n_t) - wh_t n_t - cv_t + \beta\mathbb{E}_t[\Pi(\epsilon_{t+1}, n_t)]\} \tag{10}$$

subject to the law of motion of employment:

$$n_t = (1 - \delta) \cdot n_{t-1} + q(\theta_t) \cdot v_t \tag{11}$$

The first order condition of profit maximization implicitly determines the demand for employment $n_t = n(\theta_t, h_t, w)$ of the firm.

Workers and firms negotiate hours and wages to split the surplus created by realized matches, which translates into an hours schedule and a wage schedule. Note that there are multiple hours and wage schedules that are compatible with equilibrium. At this point, we allow for general hours and wage schedules: $h(w, \theta, \epsilon, n, b, \tau, t)$ and $w(h, \theta, \epsilon, n, b, \tau, t)$.

Hours vs Employment Responses & STW policy In sections 3 to 5, we showed three important sets of empirical results regarding the hour and employment responses of firms to STW policy. First, we showed that hours decrease strongly with STW. Second, we showed that this hours decrease was met by a large positive employment response. Finally, we showed that low productivity firms are more likely to take up STW.

In Appendix D.2, we characterize the hours schedule and the firm's hours and employment responses to variation in productivity and variation in STW generosity, *conditional on the wage schedule*. This characterization of hours and employment responses to STW enables to transparently understand the conditions under which our general model delivers the observed reduced form results of sections 3 to 5. This exercize highlights the critical role of rigid wage schedules in amplifying the employment responses to STW. In particular, we show that hours decrease strongly and employment increases strongly with STW, and low productivity firms select more into STW, when four conditions are met: (i) the marginal utility of employment for workers is strongly decreasing in hours; (ii) the wage schedule is relatively rigid; (iii) technology is relatively linear in employment n but (iv) relatively concave in hours h.

The intuition for (i) is quite straightforward. When the return to an additional hours in terms of utility decreases strongly, which can be due to large risk aversion in consumption or a very convex disutility of work, STW subsidies reduce more drastically workers' reservation hours, making the hours schedule more responsive to the introduction of STW. Conditions (ii), (iii) and (iv) also have an intuitive interpretation. When productivity goes down, firms want to reduce more their labor inputs, especially when wages are rigid. The more concave technology is in hours relative to employment, the more firms want to "hoard labor" and reduce hours relative to employment. Without STW, outside option of workers reduces the extent to which firms can reduce hours, and they will reduce employment instead. With STW, firms can offer lower hours, and increase employment instead. Rigid wages magnify again this employment response: when hours decrease

in response to STW, the net profit of a filled job increases more when wages are more rigid, driving a larger positive employment response.

Interestingly, we showed clear empirical evidence that wages exhibit a significant level of rigidity in our context. This means that condition (ii) is likely to be met, and helps explaining why we find such strong and significant effects of STW on firms' hours and employment.

Equilibrium & Spillover Effects A steady state equilibrium consists in a set of: (i) hours schedules h and wage schedules w that split the surplus in high and in low productivity firms subject to the incentive constraint that $W_k^e - W^u \geq 0$; (ii) labor demand functions n^d in high and in low productivity firms that maximizes firms' profits and (iii) a labor market tightness θ that clears the labor market subject to the steady state equality of flows in and out of employment.

To understand the logic of the equilibrium effects of STW in the labor market, we borrow the equilibrium representation of Michaillat [2012]. This representation allows for a transparent representation of the effects of various labor market policies on equilibrium (e.g. Landais, Michaillat and Saez [2018a]) and of the mechanisms underlying equilibrium spillover effects across workers or firms (Lalive, Landais and Zweimüller [2015]).

In this representation, the steady state equality of flows in and out of employment characterizes a labor supply $n^s(\theta, \delta)$, which is an increasing function of θ in the $\{n, \theta\}$ space. The profit maximization of firms determines a labor demand supply $n^d(\theta)$, which will be a decreasing function of θ when the marginal product of n is decreasing, and horizontal otherwise (i.e. if technology is linear in n). With random matching, aggregate labor demand is simply the weighted sum of demands of high and low productivity firms. Equilibrium thightness and equilibrium employment are determined at the intersection of aggregate demand and supply. When STW is introduced, labor demand of low productivity firms increases, especially so when tightness is low (and hiring is therefore cheap). This in turn increases aggregate demand, and equilibrium tightness. This increase in equilibrium tightness is the force driving our observed spillover effects in the data. It makes hiring more costly for all firms, and therefore reduces employment of firms non treated by STW. This equilibrium mechanism captures the negative reallocation effects of STW which distorts employment towards low productivity firms rather than high productivity firms. Again, this effect will be stronger the more horizontal labor demands are (that is, the more linear technology is in n). A graphical illustration of these equilibrium mechanisms, using the calibrated version of our model, is offered in Appendix Figure D-1.

6.2 Optimal STW Subsidy

We now use the general model presented above to characterize the optimal STW subsidy rate and clarify the welfare trade-offs implied in STW policies.

Planner's problem The planner maximizes a utilitarian social welfare function $\Gamma(W_H^e, W_L^e, W^u, n, \rho) = n \cdot \left[\rho \cdot W_H^e + (1 - \rho) \cdot W_L^e \right] + (1 - n) \cdot W^u$, using government policies $\mathbb{T} = \{\tau, b, t\}$ where τ is the STW

subsidy rate, b is the UI benefit level given to the unemployed, and t is a lump sum tax financing both STW and UI. The planner maximizes social welfare subject to three set of constraints. First, the government budget needs to balanced. Second the government needs to account for the optimal behavior of workers and firms that are function of the policy instruments. Finally, the labor market must be in equilibrium. We further assume that profits are fully taxed and redistributed lump sum to all workers.

Proposition 1. *Assuming differentiability, an interior optimal subsidy rate τ balances the transfer value of the policy with the fiscal externality, the employment externality and the hour externality of the policy and needs to satisfy:*

$$
1 + \underbrace{\left\{ \varepsilon_{n,\tau} \frac{(1-\rho)b^{STW} - b}{b^{STW}} - \varepsilon_{h_L,\tau} \frac{h_L}{\bar{h} - h_L} \right\}}_{\text{Fiscal Externalities}} = \overbrace{\mathbb{G}_L}^{\text{Value of Transfer}} + \varepsilon_{\theta,\tau} \frac{\theta}{E} \cdot \overbrace{\left\{ \Phi'(\theta)\Delta + q'(\theta)\mathcal{C} \right\}}^{\text{Employment Externalities}}
$$

$$
+ \varepsilon_{h_L,\tau} \frac{n_L \cdot h_L}{E} \cdot \underbrace{\left\{ [F_L^h - w] + [w(1-\tau) - MRS_{c,h}^L] \cdot \mathbb{G}_L \right\}}_{\text{Hours Externalities}},
$$

(12)

where $\varepsilon_{Y,X} = \frac{dY}{dX} \frac{X}{Y}$ denote the elasticity of Y w.r.t. X. $n_L = (1-\rho)n$ is employment in low productivity firms and h_L is contracted hours in these firms. $F_L^h = \frac{\epsilon_L}{n_L} \cdot \frac{\partial F(h_L, n_L)}{\partial h}$ is the marginal product of an increase in hours in low productivity firms. $E = \tau \cdot n_L \cdot w \cdot (1 - h_L)$ is total expenditures on the STW policy. $\mathbb{G}_L$ is the social welfare weight on workers currently in low productivity firms. Δ is the weighted wedge in utility between being employed and unemployed and $\mathcal{C} = c \cdot v$ is total recruiting costs. $MRS_{c,h}^L = \frac{u_c'(c_L, h_L)}{u_h'(c_L, h_L)}$ is the marginal rate of substitution between consumption and hours for workers in low productivity firms.

Proof. *See Appendix D.3.*∎

The first two terms correspond to the traditional public finance formula for optimal tax/transfer, which simply states that, absent pre-existing distortions, the optimal transfer balances the value of the transfer with its fiscal externality at the margin. In our context, two additional sources of potential inefficiencies arise, that the planner needs to account for when setting the subsidy τ. First labor market frictions do not ensure that employment is at a socially efficient level to start with. Second, there is no market for hours.

To better understand and interpret the formula, we now turn to each of its terms separetely, and provide a local calibration of the welfare effects of a marginal change in the subsidy τ from its current level, based on our reduced-form empirical estimates of sections 3 to 5.[33]

Value of STW Transfer The social value of transferring one euro from all taxpayers to workers currently in low productivity firms is captured by $\mathbb{G}_L = \frac{\Omega_L}{n_L} \frac{u_c'(c_L, h_L)}{\mu}$ where μ is the Lagrange

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[33] All the details of the local calibration are provided in Appendix E.2.

multiplier for the budget constraint in the planner's problem, which captures the social value of one euro redistributed lump sum to all workers. Ω_L is a weight that captures the expected relative time that workers currently in a low productivity firm will spend in low vs high productivity firms or in unemployment.[34] The value of STW transfers depends critically on the marginal utility of consumption of treated workers $(u'_c(c_L, h_L))$ relative to that of the whole population of workers μ. Figure 4 panel C shows that treated workers have total earnings and transfers that are significantly below ($\approx 18\%$ lower) that of their matched non-treated workers. This indicates that their marginal utility of consumption might be significantly higher than that of the average worker. In Appendix E.2, using these estimates and a coefficient of relative risk aversion of 2.5, we calibrate $\mathbb{G}_L$ and find that the value of transfer is relatively large: $\mathbb{G}_L \approx 1.45$.

Fiscal externality Transferring one euro to workers in STW programs costs more than 1 euro, because workers and firms do not internalize the effect of their change in behaviors on the government budget constraint, which creates a fiscal externality. This fiscal externality is captured by two terms. The first term, $\varepsilon_{n,\tau} \frac{(1-\rho)b^{STW}-b}{b^{STW}}$ captures the cost to the government of employment responses. When employment increases in response to an increase in τ, $(\varepsilon_{n,\tau} > 0)$, this moves individuals out of unemployment, which saves the government on the unemployment benefits b they collected. But it also increases the number of individuals receiving STW benefits b^{STW}. The relative generosity of STW vs UI benefits and the fraction of workers in low productivity firms therefore determine the sign of this fiscal externality. When UI benefits are very generous and the fraction of workers in low productivity firms receiving STW is small, the employment responses may have a positive effect on the government's budget. The second term captures the hours response to the program: $-\varepsilon_{h_L,\tau} \frac{h_L}{h-h_L}$. Because of the large negative responses of hours to the policy $\varepsilon_{h_L,\tau} \approx -.4$, this term increases the fiscal externality of STW significantly. Using our estimates, we show in Appendix E.2, that the total estimated fiscal externality is quite large, and equal to .37. Interestingly, it is quite close to the calibrated value of the transfer. This means that the welfare value of a marginal increase in the subsidy rate above its current level would be quite small, unless the hours and employment externality terms are very large. To investigate this, we now turn to these two extra externality terms.

Employment Externalities Our empirical evidence shows that STW affects equilibrium employment, creating employment spillovers on untreated firms. As shown in Landais, Michaillat and Saez [2018a], in frictional labor markets, such equilibrium effects have potential welfare consequences, and the design of labor market policies need to account for them. The reason is that in frictional labor market, market tightness θ, and, as a consequence equilibrium employment, need not be at their socially efficient level, which is defined by the Hosios condition (Hosios [1990]). Here, the Hosios condition will hold when the term $\left\{ \Phi'(\theta)\Delta + q'(\theta)\mathcal{C} \right\}$ is equal to zero. This term

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[34]If on average more time is spent in, say, the low productivity state, then the social planner places greater weight on welfare in this state. The precise definition of the weights is provided in Appendix D.3.

captures the competing search externalities created by a change in equilibrium tightness. On the one hand, an increase in θ will increase the probability for workers to find jobs ($\Phi'(\theta) > 0$), and being employed gives them an increase in utility equal to the wedge between the average utility of being employed vs unemployed Δ. On the other hand, an increase in θ will decrease the probability that the firms's vacancies are matched ($q'(\theta) < 0$), increasing the overall cost $\mathcal{C}$ of replacing workers for firms.[35] In specific models (directed search for instance), these two opposite externalities may exactly cancel out. But in general, there is no particular reason for the Hosios condition to hold. If we believe that equilibrium employment is suboptimally low in Recessions, then any policy increasing labor market tightness like STW may have positive employment externalities that are socially desirable.

While it is tricky to calibrate the Hosios term, in Appendix E.2 we use our reduced-form estimates to provide evidence that (i) the curvature of the matching function is large, and that (ii) the utility wedge between employment and unemployment is large. These two facts indicate that the employment externality is likely to be positive, suggesting that employment is indeed suboptimally low during recessions.

Hours Externalities Incorporating the intensive margin of hours in the model has important welfare implications as the missing market for hours creates an additional source of externalities that the planner needs to account for. While hours and wages are set to split the surplus between workers and firms, there is no reason for hours to be set at the socially efficient level. As is clear from our formula, hours are at the first best optimum when the marginal rate of substitution $MRS_{c,h}^L$ is equal to the marginal rate of transformation (the marginal product of an hour F_L^h) and equal to the wage rate w. In some models, such as directed search, hours will be optimally set at the first best. But this is not always the case in our more general framework. If equilibrium hours deviate from this level, the large negative effect of STW on equilibrium hours ($\varepsilon_{h_L,\tau} < 0$) entails welfare effects.

As we discuss in Appendix E.2, signing and calibrating the hours externality term remains tricky in practice. On the one hand, the large employment responses to the reduction in hours in firms treated by STW indicates that $[F_L^h - w] < 0$. On the other hand, there is ample evidence that the fraction of workers reporting that they are willing to work more hours increases drastically during recessions (e.g. Canon, Kudlyak and Reed [2014]). This would indicate that $w(1-\tau) - MRS_{c,h}^L \geq 0$. In which case decreasing equilibrium hours has a negative externality on workers.[36]

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[35]Note that Δ will be larger in the presence of specific human capital, or experience effects. But the cost of replacing a worker with a similarly productive one $\mathcal{C}$, will also be larger when it is hard to find similar workers due to specific human capital, experience effects. It is therefore unclear how the presence of experience effects or specific human capital affects the socially efficient level of tightness and the optimal level of the subsidy τ.

[36]This effect on welfare is weighted by the social marginal welfare weight of workers in low productivity firms experiencing this decline.

6.3 Calibration & Counterfactual Policy Analysis

The previous characterization of the optimal STW subsidy is useful to clarify the trade-offs involved in STW policies in the general class of search-and-matching models we presented, and get a sense of the welfare consequences of local deviations from the existing policy. We now turn to a structural calibration of our model. While this calibration comes at the cost of putting more assumptions on the structure of the model, it delivers the additional benefits of enabling the exact computation of the externality terms in formula (12), which can be hard to measure empirically. More importantly, it allows the counterfactual explorations of non-local policy changes, such as removing STW.

When specifying the model for the purpose of calibration, we make a series of assumptions. In particular, we assume that in low productivity firms, all the bargaining power is on the firm's side, so that all the surplus goes to the firms and workers are kept at their outside option. Besides greatly simplifying the computation of the hours schedule, a useful byproduct of this modelling feature is that it generates quite large variations in bargained hours in response to STW. For wages, we assume that they are a somewhat rigid function of productivity, and, following our empirical evidence, that they do not respond to the STW policy.[37]

All further details on functional form specifications and parameter calibrations are given in Appendix E.2. Importantly, we explain in this Appendix section how our reduced-form empirical evidence, using quasi-experimental variation, allows us to calibrate most of the key parameters of the model. In particular, parameters of the demand function can be identified by the reduced form evidence of the hours and employment responses of firms to STW treatment. Second, our reduced form evidence on spillover effects identifies key parameters of the matching function. Final parameters of model, that cannot be identified from quasi-experimental variation, nor directly calibrated from external sources, are estimated using GMM to match a set of key moments of firms above 15 FTE eligible to STW during the Great Recession. In effect, our calibration relies on the thought experiment that we have a version of the Italian economy where all firms correspond to firms above 15 FTE, and are eligible to STW. Furthermore, we treat the overall period 2008-2014 of the Great Recession as a steady state equilibrium.

In Figure 7, we display results of a counterfactual analysis of this steady state equilibrium during the recession, for various levels of the STW subsidy τ. Panel A shows that a higher STW subsidy significantly decreases the level of unemployment. In particular, in the absence of any STW subsidy ($\tau = 0$), the unemployment level would have been almost 2 percentage point higher during the recession. As shown in panel C, this comes at the cost of a significant decline in total TFP of about 2%. Yet, overall, panel D shows that the total welfare effect of having STW is positive: compared to a situation without STW, welfare was about 2% higher during the recession. Results also confirm that the marginal welfare effect of increasing or decreasing the subsidy is close to zero. The reason is that the subsidy is already large enough that workers are willing to accept extremely low hours: Panel B shows that, at $\tau = .8$, the hours constraint on low productivity firms

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[37]As in Hall [2005] or Landais, Michaillat and Saez [2018b], we assume a wage schedule of the following form $w(\epsilon) = w_s \epsilon^{w_a}$, with $w_a < 1$.

does not bite any longer, so that any further increase in the subsidy does not affect the hours and employment allocation any more.

The previous calibration considers the Great Recession in Italy as a steady state, and asks what the value is, in such a steady state, of having STW subsidies target firms with negative idiosyncratic shocks. But the nature of shocks, whether they are permanent or transitory, aggregate or idiosyncratic, may matter as well in assessing the effects of STW policies. Firms may be more willing to hoard labor when they expect a shock to be temporary, and therefore relaxing constraints to labor hoarding may be more effective for temporary shocks.[38] To get further insights on this, in Appendix F.3, we use our calibrated model and simulate the effects of STW under two different scenarii of aggregate shocks: a permanent shock and a transitory shock.

Results, reported in Appendix Figure F-1 show that hoarding is indeed more valuable when the shock is transitory than permanent, and that labor hoarding is significantly larger when the cost to firms of replacing their workers increases. As a consequence, the employment effects of having STW also differ according to the permanence of the aggregate shock. The employment effects of STW on impact are significantly larger (around 20% to 40%) when the shock is temporary than when it is permanent. This, again, is especially true when the cost of replacing workers is high, and when the magnitude of the aggregate shock is large.

These counterfactual simulations help put into perspective our empirical results, and gauge their external validity outside the Italian context of the Great Recession. In particular, they help explain why the effectiveness of STW may have proved very different in Italy compared to other countries such as Germany during the Great Recession. First, the recession was a very transitory and very large shock in Germany (due to the collapse of world trade in 2009) and a much longer and protracted shock in Italy (due to the European debt crisis that followed). Second it is mostly high productivity exporting manufacturers that were affected in Germany, with high skilled workers that are very costly to replace, while, as we showed, it is mostly low productivity firms with lower skilled workers that were affected in Italy. This suggests that STW might have been much more effective in the German context than in Italy during the Great Recession.

7   Concluding Remarks

STW programs have attracted a lot of attention as a tool to subsidize labor hoarding, and have been aggressively used during the Great Recession. Yet, very little is known on their effects and welfare consequences. This paper contributes by providing new high quality administrative data, a compelling quasi-experimental setting and a general framework to interpret our results. We show that STW has large, but temporary effects on labor inputs, and no significant long run insurance value to workers. We provide evidence that the dynamics of these effects has to do with the particular selection of firms into STW and the nature of the shock they face. Furthermore, we

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[38]Our previous analysis in Figure 5 indeed indicates that employment effects of STW are larger for firms that were high productivity prior to the recession, suggesting that STW may be more effective for high productivity firms experiencing a transitory negative shock than for permanently low productivity firms.

show that STW does significantly affect reallocation in the labor market.

Our framework then enables to use this empirical evidence to characterize the welfare consequences of STW. We derive a formula for the optimal STW subsidy in a general class of search and matching models. The fundamental insight is that, above the traditional trade-off between the value of transfers and fiscal externalities, STW will entail positive welfare gains when equilibrium employment is suboptimally low, and hours suboptimally high. Importantly, our formula offers a clear representation of these hours and employment inefficiency terms that connects to the data. The advantage of this approach is that the formula, and the key tradeoffs underpinning it, remain the same irrespective of the exact structure and primitives of the underlying model. In that sense, our formula is robust to the way wages and hours are determined in the model, to the specification of the costs of replacing or firing workers, to the presence of specific human capital, to various sources of hours or wage rigidity, to the presence of liquidity constraints, etc. Based on our empirical evidence, we show that STW has positive, albeit small, welfare effects. While more work needs to be done to better understand STW programs, the calibrated version of our model already enables to explore the validity of our findings outside the Italian context, and suggests that STW will be significantly more effective for large but transitory shocks in context where labor hoarding is constrained by wage rigidities, hours rigidities or financial rigidities.

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Figure 1: FIRM'S & WORKER'S PROBABILITY OF RECEIVING SHORT TIME WORK TREATMENT BY FIRM SIZE AND SECTOR:

A. Firm

B. Workers
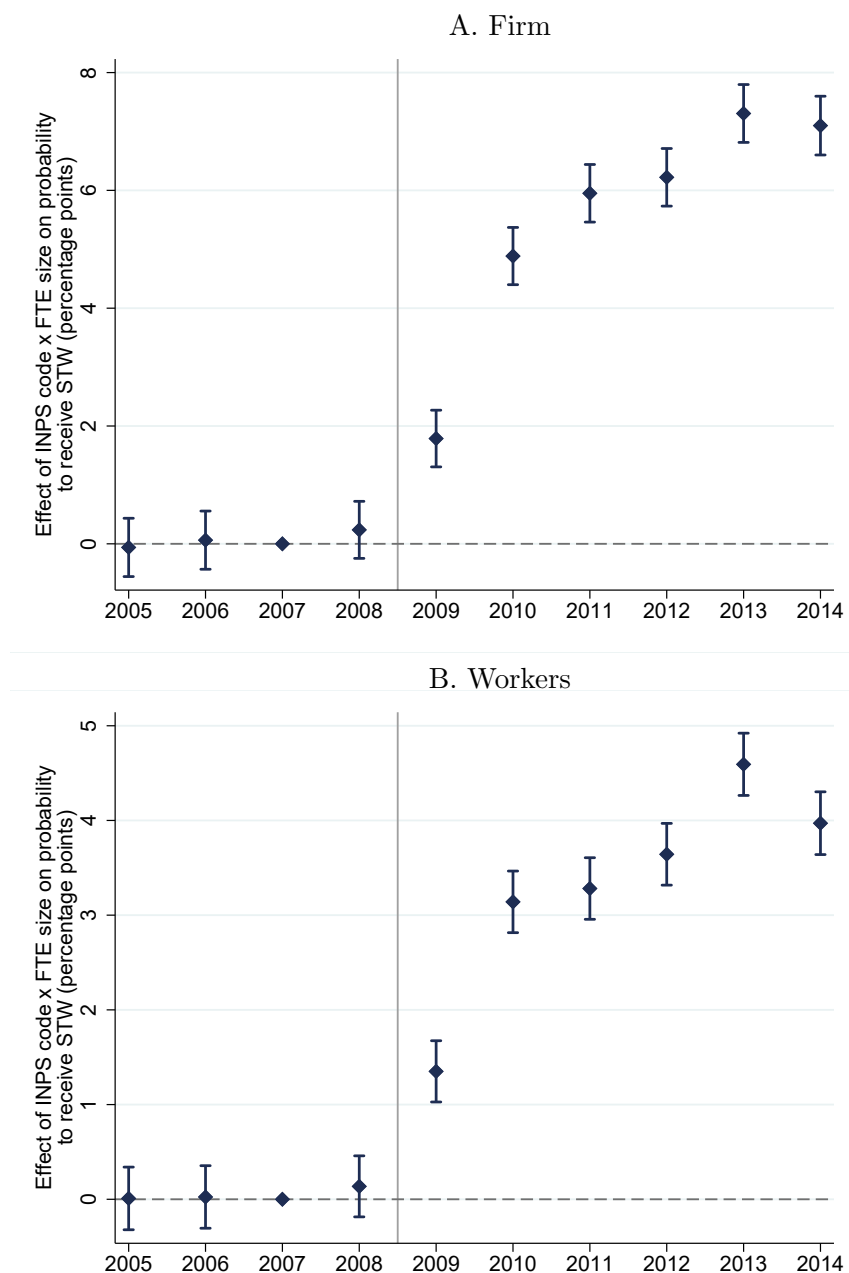
Notes: The graphs show the coefficients $\hat{\gamma}_1^t$ estimated from equation 1 for all years $t \in [2005, 2014]$ using the probability of STW receipt as outcome. The omitted year is 2007, so all results are relative to 2007. Panels A and B plot the estimated coefficients for the probability of STW receipt at firm level and at worker level respectively. We cluster standard errors at the INPS code times firm size group level. The vertical bars indicate 95% confidence intervals. See text for details.

Figure 2: Estimates of the Effects of Short Time Work on Firms' Outcomes
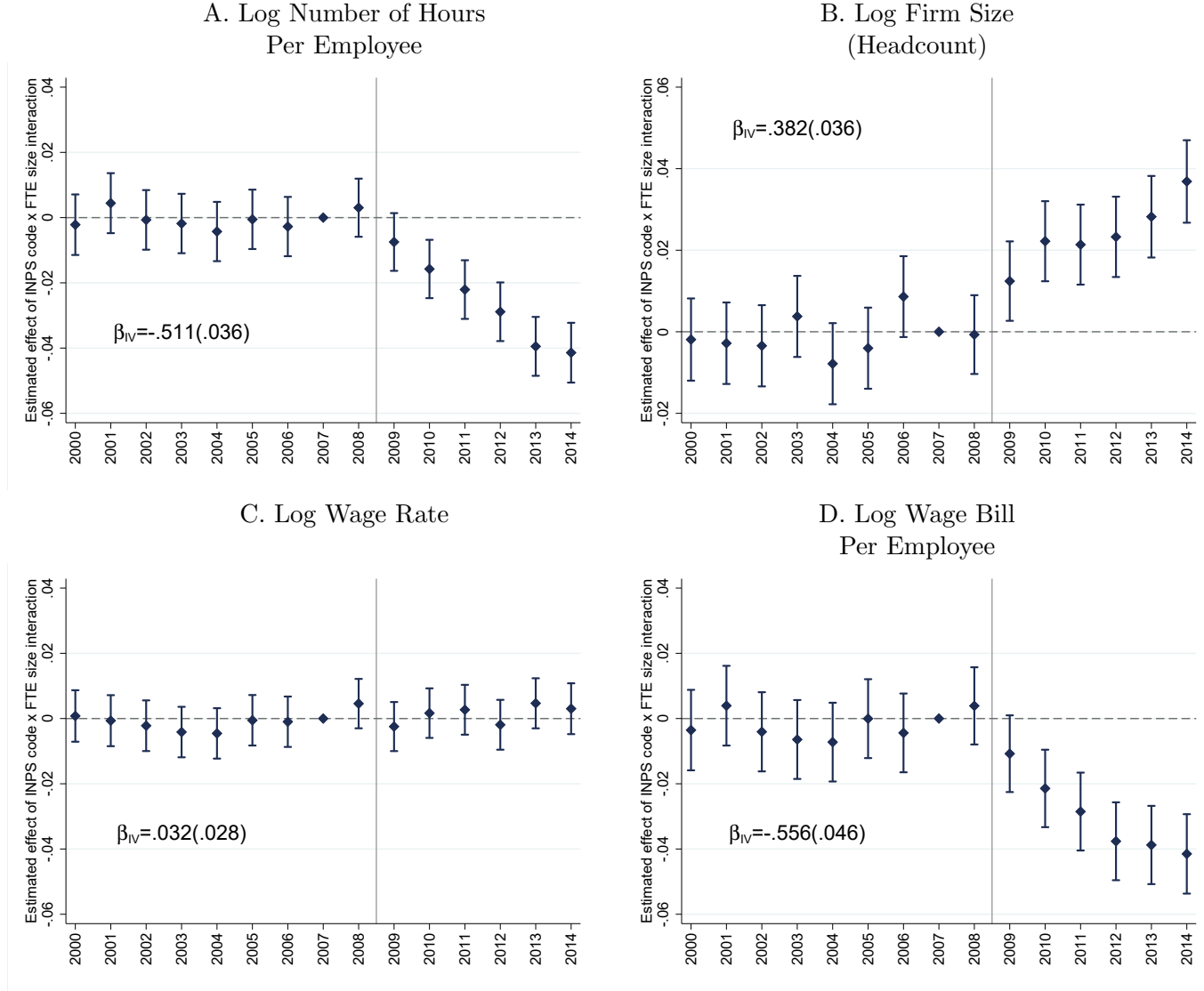
A. Log Number of Hours
Per Employee

B. Log Firm Size
(Headcount)

C. Log Wage Rate

D. Log Wage Bill
Per Employee

Notes: The graphs show the coefficients $\hat{\gamma}_1^t$ estimated from equation 1 for all years $t \in [2000, 2014]$ for different firm-level outcomes. The omitted year is 2007, so all results are relative to 2007. We cluster standard errors at the INPS code times firm size group level. The vertical bars indicate 95% confidence intervals based on cluster-robust standard errors. Each graph also reports the coefficient $\hat{\beta}_{IV}$ estimated from equation 2 and its associated standard error. The wage rate is defined as earnings per hour worked per employee.

Figure 3: TOT ESTIMATES OF THE DYNAMIC EFFECTS OF SHORT TIME WORK: LOG NUMBER OF HOURS
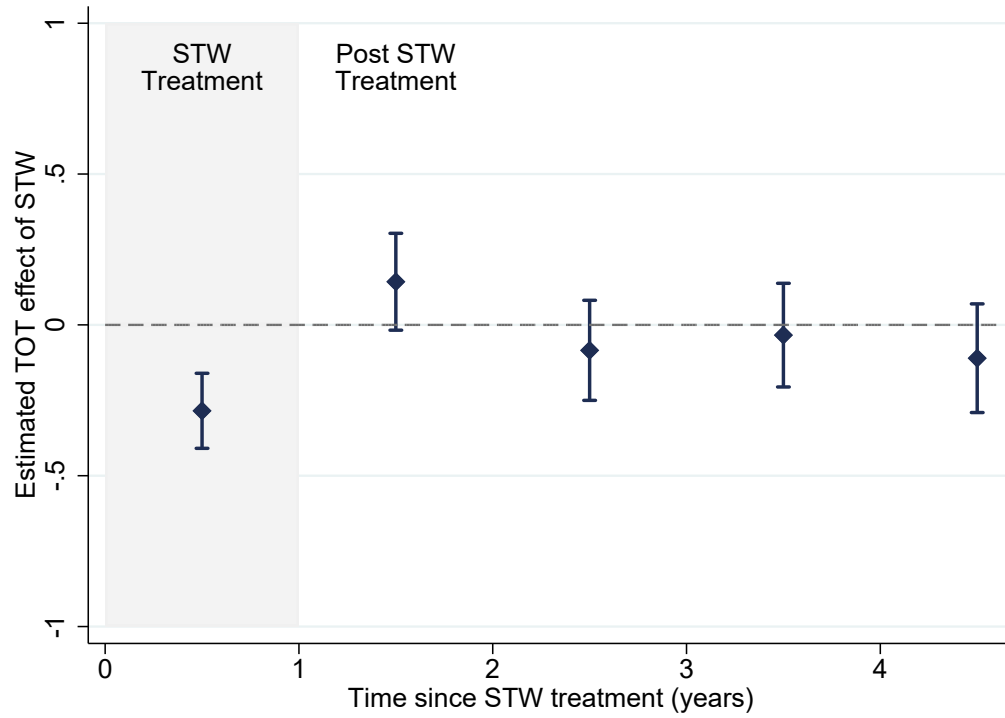
Notes: The graph reports the coefficients $\hat{\beta_k^{TOT}}$ for $k \in [0, ..., 4]$ for the dynamic effects of STW treatment on hours worked per employee. These effects are estimated recursively as illustrated in Appendix A.2. The β_k^{TOT} coefficients identify the dynamic treatment effects of STW receipt in year $k = 0$ on outcomes in years $k \in [0, ..., 4]$. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. See text for details.

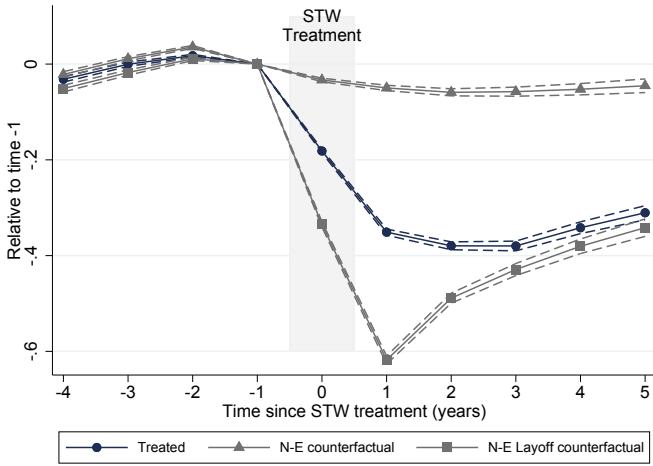Figure 4: Dynamic Effects of CIGS treatment on workers' outcomes

A. Probability of Employment
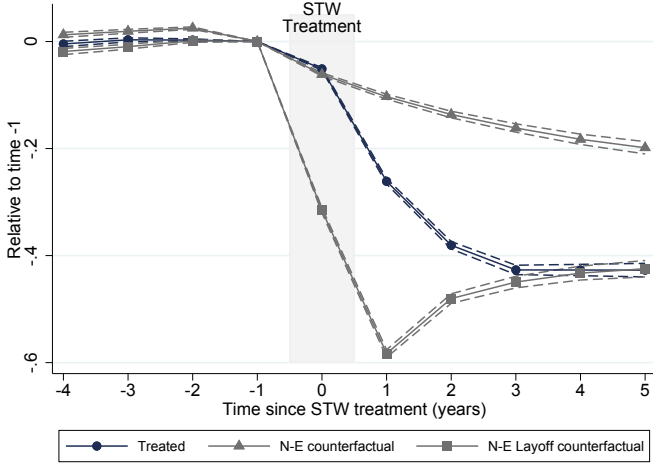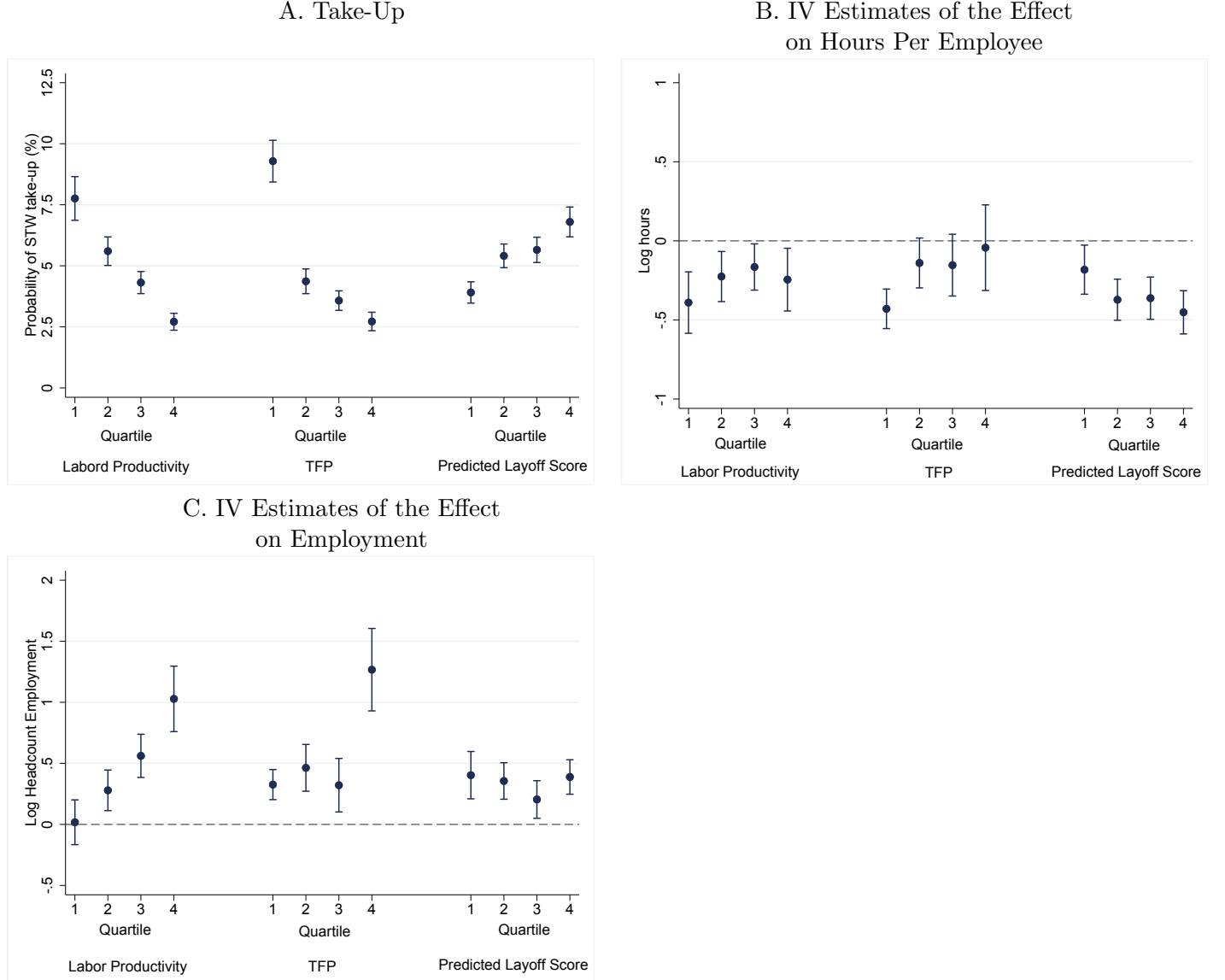
B. Number of Hours Worked
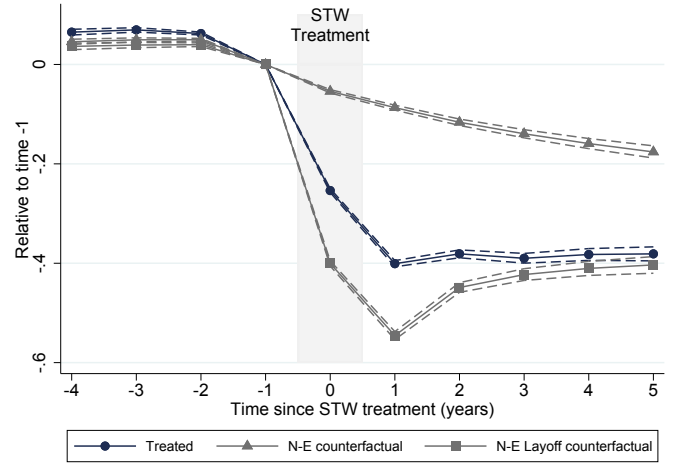

C. Earnings + CIGS/Transfers

Notes: The graphs report the estimated coefficients of event study regressions for different outcomes and different event-year definitions at the worker level. All estimates are relative to event-year -1 and are scaled by the average level of the outcome in that year. Individual and calendar year fixed effects are included in the event-time specification. The dashed lines around the estimates indicate 95% confidence intervals based on robust standard errors clustered at the individual level. For the treatment group (indicated by solid circles), an event year is defined as the first year in which the worker experiences a STW event, conditional on the worker being in a firm with 6-month average FTE size $\in (15; 25]$ at event time -1. The first comparison group (indicated by solid triangles) consist of workers employed at firms with 6-month average FTE size $\in (5; 25]$ at event time -1, which are not eligible for STW due to either their INPS code or FTE size. The second comparison group (indicated by solid squares) consist of workers employed at non-eligible firms with 6-month average FTE size $\in (5; 25]$ at event time -1 and who experience a layoff in event time 0. Individuals in the two comparison groups are matched to individuals in the treatment group using Mahalanobis nearest-neighbor matching without replacement based on gender, age, job characteristics at event time -1, employment status, annual weeks worked, earnings and firm size at event times -1, -2, -3 and -4, and main industry at event time-1. Total hours worked and total earnings are unconditional on employment.

Figure 5: SELECTION OF FIRMS INTO STW AND HETEROGENOUS TREATMENT EFFECTS

A. Take-Up

B. IV Estimates of the Effect
on Hours Per Employee

C. IV Estimates of the Effect
on Employment

Notes: The graphs show heterogeneity in STW take-up and treatment effects across different firm characteristics. Panel A displays the estimated $\hat{\kappa}_1$ from specification 3 for the probability of STW take-up for groups of firms with different levels of productivity and with different predicted likelihood of mass layoffs. For productivity, firms are ranked into four quartiles of the distribution of average yearly productivity in 2007-2008. Productivity is measured as labor productivity (defined as value added per week worked) or total factor productivity (defined as described in section 3.2). Firms are also ranked into quartiles of the distribution of their predicted probability of mass layoff, as described in section 5.1. The vertical bars indicate 95% confidence intervals based on cluster-robust standard errors. Panels B and C report the estimated $\hat{\beta}_{IV}$ from specification 2 for the log of total annual hours worked per employee and the log of total employment headcount. The two panels are constructed in the same way as Panel A. See text for details.

Figure 6: REALLOCATION EFFECTS: EMPLOYMENT GROWTH OF NON-ELIGIBLE FIRMS AS A FUNCTION OF STW TREATMENT IN THE LOCAL LABOR MARKET

A. Employment Growth
2005-2008 to 2010-2013

B. Placebo: Employment Growth
2000-2005 to 2005-2008
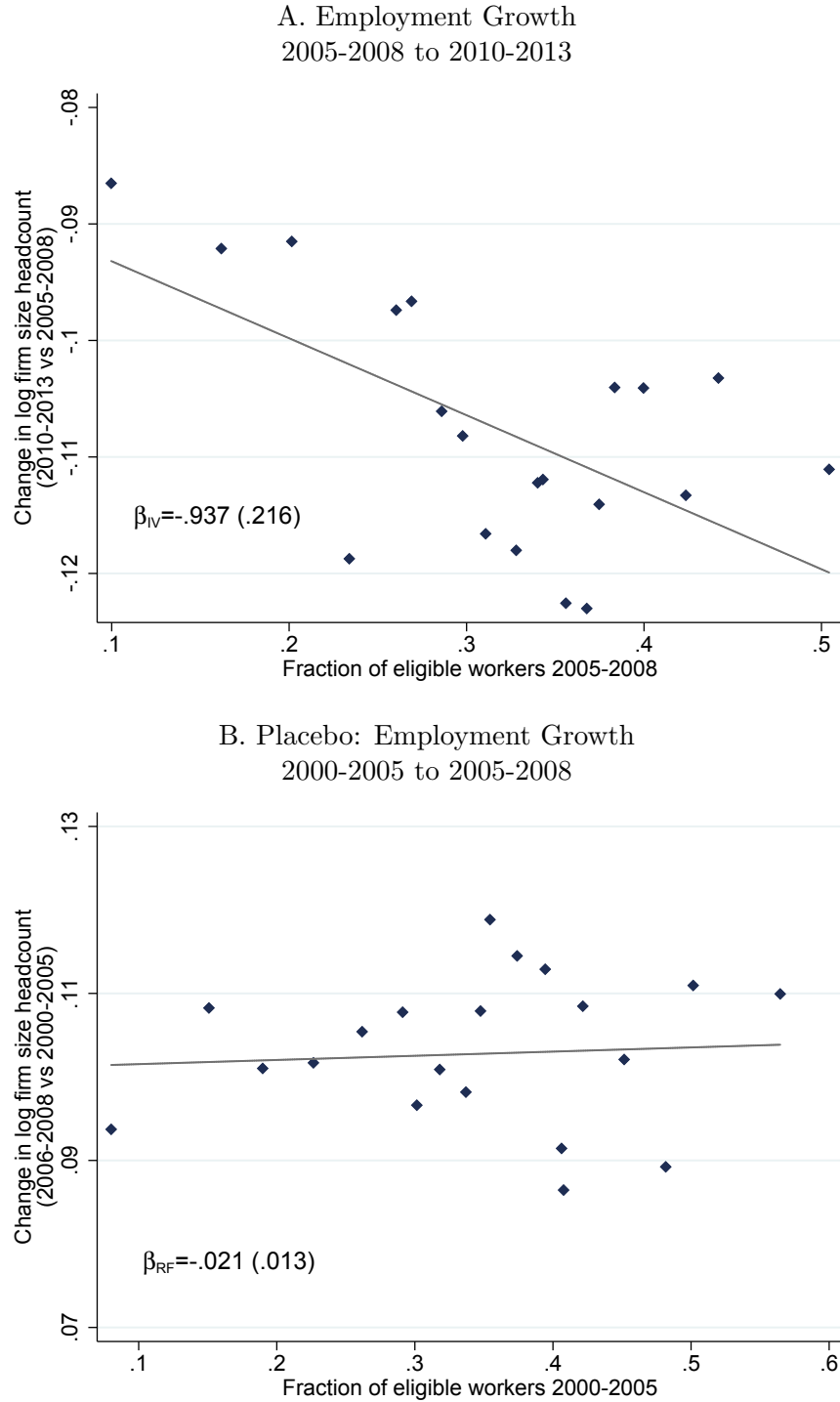
Notes: The graphs show binned scatterplots of the reduced form of equation 7. Panel A plots the reduced form relationship between the change in average log firm size headcount of firms non-eligible to STW in a local labor market (LLM) between 2005-2008 and 2010-2013, and the fraction of eligible workers in 2005-2008 in the LLM based on the interaction between firm size and INPS codes. Both variables are residualized on firm level and LLM level controls (see text for details). Panel A also reports the $\hat{\beta}_{IV}$ coefficient from equation 7 and its associated cluster robust standard error in parenthesis. Panel B is constructed in the same way as Panel A and shows the placebo relationship between the change in average log firm size headcount of firms non-eligible to STW in a LLM between 2000-2005 and 2005-2008, and the fraction of eligible workers in 2000-2005 in the LLM. Panel B also reports the reduced-form $\hat{\beta}_{RF}$ coefficient from equation 7 and its associated cluster robust standard error in parenthesis.

Figure 7: Counterfactual simulations: effects of changing STW generosity τ

A. Unemployment

B. Hours

C. Total Factor Productivity

D. Welfare
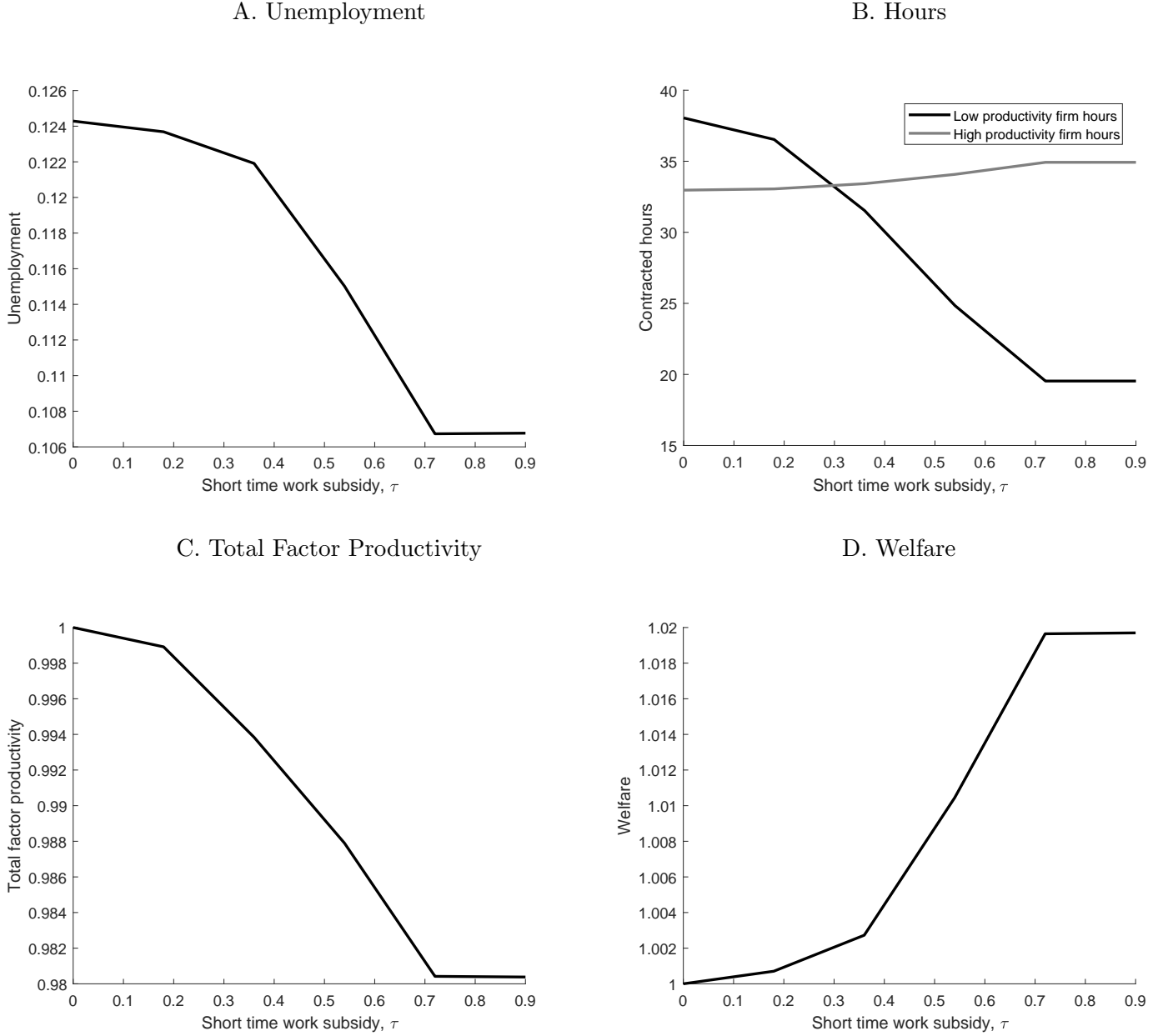
Notes: The Figure displays results of a counterfactual analysis of steady state equilibria of the Italian economy during the Great Recession using our calibrated model and varying the level of the STW subsidy τ. Panel A shows counterfactual values of the equilibrium unemployment rate, panel B displays counterfactual values of the hours per employee for low and high productivity firms. Panel C shows the counterfactual values of total factor productivity. Panel D shows counterfactual values of total welfare (i.e. including firms profits which are rebated lump sum to workers). For panel C and D, results are normalized to the level of the outcome in the steady state equilibrium without STW (τ=0). All details of the calibration of the model are given in Appendix E.2.

Table 1: Effects of STW Treatment on Firm and Worker's Outcomes

	IV Estimate	Std Error	N
	A. First Stage		
Proba. of CIGS Take-Up	.05	(.002)	3029855
	B. Employment Outcomes		
Log Number of Hours Per Employee	-.511	(.036)	2843205
Log Number of Full-Time Weeks Per Employee	-.461	(.034)	2843205
Log Firm Size (Headcount)	.382	(.036)	2843205
Log Wage Rate	.032	(.028)	2843205
Log Wage Bill Per Employee	-.556	(.046)	2843205
Log Number of Open-Ended Contracts	.432	(.047)	2843205
Log Number of Fixed-Term Contracts	-.367	(0.128)	2843205
Firm Survival Probability (in $t+1$)	-.014	(.009)	2570917
	C. Balance-Sheet & Productivity Outcomes		
Firm Value-Added	.095	(.159)	873839
Value-Added Per Worker	-.508	(.120)	873839
Labor Productivity	-.142	(.104)	873839
Total Factor Productivity	-.056	(.143)	873839
Liquidity	.939	(.461)	873839

Notes: Panel A reports the $\hat{\kappa}_1$ coefficient estimated from 3 and its associated robust standard error in parenthesis. Panels B and C report the $\hat{\beta}_{IV}$ coefficients estimated from equation 2 and their associated robust standard errors in parenthesis for a set of different firm-level outcomes. The wage rate is defined as total earnings per week worked per employee. For survival probability, the reported coefficient is the IV estimate scaled by average survival probability in $t+1$: $\hat{\beta}_{IV}/\bar{Y}$. Value added is defined as total revenues plus unsold stocks minus cost of goods and services used in production, or equivalently total profits plus total capital depreciation and total wage costs. Labor productivity is value added divided by the total number of weeks worked in the firm. Total factor productivity is defined in section 1. Liquidity is defined as cash and cash equivalents.

Table 2: Robustness of Baseline Effects

	(1) "Doughnut" Regression	(2) Only ≤ 15 FTE	(3) Only >15 FTE	(4) Permutation Test	(5) No Dismissal Rule Change >60FTE Across Italy	(6) 50FTE threshold
		(Placebo)		(Placebo)		
			First Stage			
Proba. of	.053	.002	.051	.000	.055	.041
CIGS Take-Up	(.002)	(.000)	(.002)	(.000)	(.005)	(.004)
			Outcomes			
	IV	RF	IV	RF	IV	IV
Log Hrs per wker	-.449	-.011	-.602	.000	-.670	-.156
	(.037)	(.020)	(.081)	(.010)	(.230)	(.132)
Log Empl.	.284	-.020	.306	-.001	.848	.338
	(.032)	(.030)	(.099)	(.009)	(.297)	(.258)
Log Wage Bill	-.544	-.026	-.498	.000	-.568	-.390
	(.049)	(.030)	(.155)	(.013)	(.297)	(.709)
N	2686140	2608383	429490	2978239	152753	44793

Notes: The upper panel of the table reports the estimated $\hat{\kappa}_1$ coefficient from 3. Robust standard errors are reported in parenthesis below each coefficient. The lower panel reports either reduced form or IV coefficients for different firm-level outcomes. Column (1) reports the coefficients of a doughnut version of specification 2 excluding firms with 6-month average FTE size $\in (12, 18]$. Column (2) reports the reduced-form coefficient $\hat{\alpha}_1$ for specification 4 restricting the sample to firms with 6-month average FTE size $\in (5, 15]$. Column (3) reports the IV coefficients for specification 4 restricting the sample to firms with 6-month average FTE size $\in (15, 25]$ and instrumenting STW take-up with $\{\mathbb{1}[g \in \mathcal{E}] \cdot \mathbb{1}[t \geq 2009]\}$. Column (4) reports reduced-form coefficients for a placebo-version of specification 2 in which the sample is restricted to firms with non-eligible INPS codes and placebo "eligibility" status is assigned to a randomly chosen subgroup of INPS codes. Column (5) reports the estimated IV coefficients for specification 2 for a sample of establishments with 6-month FTE size $\in (0, 40]$ that belong to multi-establishment firms with FTE size > 60. For this group of firms, employment protection legislation does not apply differentially for firms above and below the 15 threshold. Column (6) reports the estimated IV coefficients for specification 2 for a sample of firms with INPS codes in the retail sectors and with 6-month FTE size $\in (25, 75]$. For this small group of firms, the size threshold that determines eligibility is set at 50.

Table 3: Equilibrium Effects of STW on Non-Treated Firm Outcomes

	Reallocation Effects			Placebo Estimates		
	IV	IV	IV	RF	RF	RF
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Employment Spillovers on Non-Eligible Firms					
Log Employment	-0.492	-0.918	-0.937	-0.021	-0.021	-0.021
	(0.137)	(0.216)	(0.216)	(0.013)	(0.013)	(0.013)
Log Inflows	-3.594	-4.406	-3.176	-0.047	-0.046	-0.030
	(1.947)	(2.380)	(1.440)	(0.112)	(0.113)	(0.107)
LLM Controls		×	×		×	×
Firm-level Controls			×			×
N		3023166			2784567	
	B. Labor Market Effects on Productivity					
Log TFP	-2.307	-2.093		-0.161	-0.161	
	(0.593)	(0.606)		(0.129)	(0.129)	
LLM Controls		×			×	
N		1222			1222	

Notes: Columns (1)-(3) of the table report the $\hat{\beta}_{IV}^{R}$ estimated from equation 7 and its associated robust standard errors clustered at the LLM level in parenthesis. Columns (4)-(6) report reduced-form placebo estimates of equation 7 comparing outcome growth during two placebo pre-recession periods (2000-2005) and (2005-2008). LLM controls are the unemployment rate and the firm size and industrial composition of employment (employment shares by industry) in the LLM in the pre-recession period. Firm-level controls are the probability of STW take-up, firm size in 2008, a dummy for whether the firm ever has an eligible INPS code and 5-digit industry dummies.

Appendix A: Additional Figures & Tables

A.1   Descriptive Statistics

Table A-1: Distribution of firms' characteristics in main sample, broken down across eligible and non-eligible INPS codes (2008)

	(1)		(2)		(3)	
	All INPS codes		Eligible INPS codes		Non-eligible INPS codes	
	mean	sd	mean	sd	mean	sd
Employees (headcount)	8.72	5.16	9.78	5.55	8.22	4.90
Employees (FTE)	8.04	4.78	9.35	5.38	7.42	4.33
Employees on open-ended contracts	7.80	4.91	8.96	5.35	7.25	4.60
Employees on fixed-term contracts	0.92	2.11	0.81	1.78	0.98	2.25
Annual hours worked per employee	2015.26	1008.70	2043.69	980.97	2001.86	1021.24
Annual wage bill per employee (000)	20.66	12.38	22.49	13.22	19.80	11.86
Net revenue per week worked (000)	6.22	49.55	5.94	52.77	6.48	46.31
Value added per week worked (000)	1.11	11.36	1.22	14.41	1.01	7.42
Liquidity	0.11	0.14	0.09	0.13	0.12	0.15
Investment in tangible assets	0.07	0.11	0.07	0.10	0.07	0.11
Investment in intangible assets	0.02	0.05	0.01	0.04	0.02	0.06
North-West	0.29	0.46	0.30	0.46	0.29	0.46
North-East	0.25	0.43	0.20	0.40	0.27	0.44
Center	0.21	0.40	0.20	0.40	0.21	0.41
South	0.25	0.43	0.30	0.46	0.23	0.42
Observations	321580		102757		218823	

Notes: The table reports the mean and standard deviation of a set of firm-level variables for firms in our sample as of 2008. The summary statistics refer to year 2008. Column (1) refers to both firms with eligible and non-eligible INPS codes. Column (2) restricts the sample to firms with eligible codes and column (3) to firms with non-eligible codes. Revenue, value-added, liquidity and investments come from the CERVED data which covers approximately 50% of firms in our sample. Value added is defined as total revenues plus unsold stocks minus cost of goods and services used in production, or equivalently total profits plus total capital depreciation and total wage costs. Liquidity is defined as cash and cash equivalents. All monetary figures are expressed in 2008 euros. North-West, North-East, Center and South are dummies for the geographic region of location of the firm within Italy.

Table A-2: DISTRIBUTION OF WORKERS' CHARACTERISTICS IN MAIN SAMPLE, BROKEN DOWN ACROSS ELIGIBLE AND NON-ELIGIBLE INPS CODES (2008)

	(1)		(2)		(3)	
	All INPS codes		Eligible INPS codes		Non-eligible INPS codes	
	mean	sd	mean	sd	mean	sd
Proportion female	0.38	0.48	0.24	0.43	0.45	0.50
Age	36.89	10.72	38.53	10.51	36.04	10.72
Proportion aged <40	0.57	0.49	0.51	0.50	0.60	0.49
Proportion aged 40-54	0.35	0.48	0.40	0.49	0.33	0.47
Proportion aged 55+	0.08	0.26	0.09	0.29	0.07	0.25
Experience (years)	14.23	10.58	16.04	10.81	13.30	10.34
Tenure (months)	59.49	71.52	66.72	76.83	55.75	68.31
Annual labor earnings (000)	15.89	10.57	18.31	11.20	14.63	10.01
Annual hours worked	1516.63	689.02	1637.52	627.07	1454.19	710.92
Proportion on full-time contract	0.82	0.38	0.90	0.30	0.78	0.42
Proportion on open-ended contract	0.83	0.37	0.88	0.32	0.81	0.40
Proportion on fixed-term contract	0.15	0.36	0.12	0.32	0.17	0.38
Proportion on seasonal contract	0.02	0.13	0.00	0.05	0.02	0.15
Proportion blue collar	0.64	0.48	0.69	0.46	0.61	0.49
Proportion white collar	0.27	0.44	0.24	0.43	0.28	0.45
Proportion manager	0.00	0.05	0.00	0.06	0.00	0.05
Proportion apprentice	0.07	0.26	0.05	0.22	0.09	0.28
Proportion native born	0.84	0.36	0.85	0.36	0.84	0.37
Observations	3350203		1140981		2209222	

Notes: The table reports the mean and standard deviation of a set of worker-level variables for workers who are employed at firms in our sample at some point during year 2008. The summary statistics refer to year 2008. Column (1) refers to workers in both firms with eligible and non-eligible INPS codes. Column (2) restricts the sample to workers in firms with eligible codes and column (3) to workers in firms with non-eligible codes.

A.2 Identification & Robustness: Additional Evidence

Figure A-1: FRACTION OF FIRM'S RECEIVING SHORT TIME WORK TREATMENT BY FIRM SIZE & INPS CODE

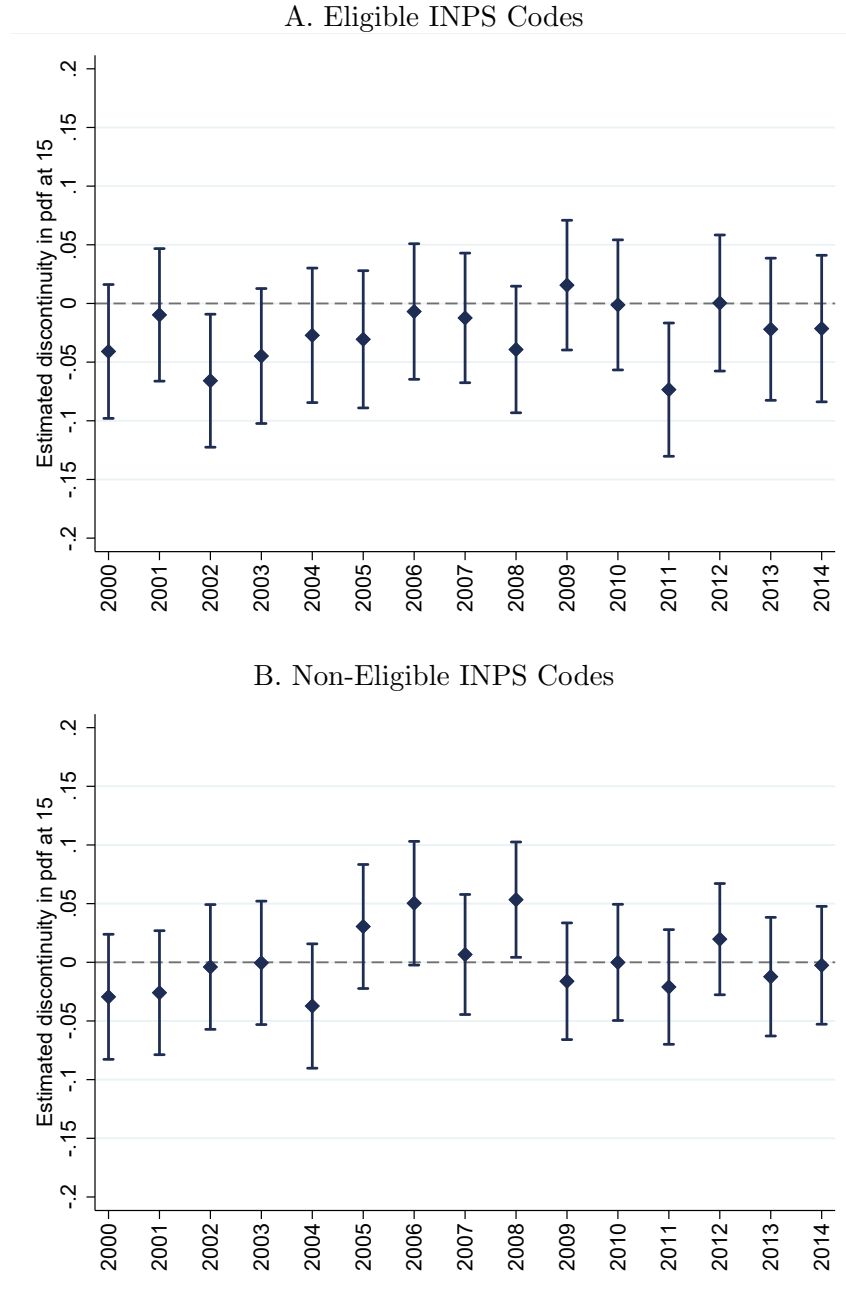### A. Eligible INPS codes

B. Non-eligible INPS codes
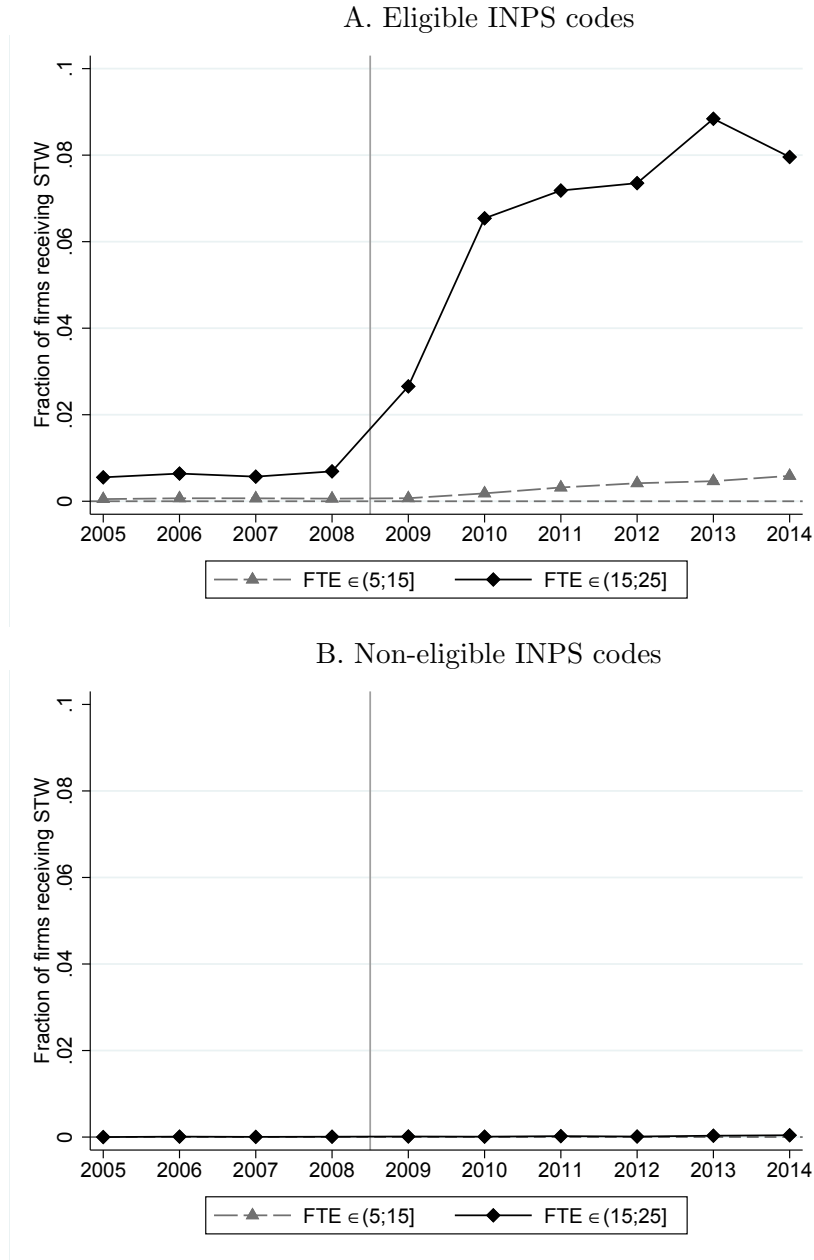
Notes: The graphs show the fraction of firms receiving STW in each calendar year $t \in [2005, 2014]$ by eligibility status and maximum 6-month average FTE firm size. Panel A plots, among firms with eligible INPS codes in our sample, the evolution of the fraction of firms receiving STW in each calendar year t from 2005 to 2014, for firms with a maximum 6-month average FTE size $\in (15, 25]$ in year t and for firms with a maximum 6-month average FTE size $\in (5, 15]$ in year t. Panel B replicates Panel A for firms in non-eligible INPS codes.

Figure A-2: DISTRIBUTION OF FIRMS' FTE SIZE (2000-2015)
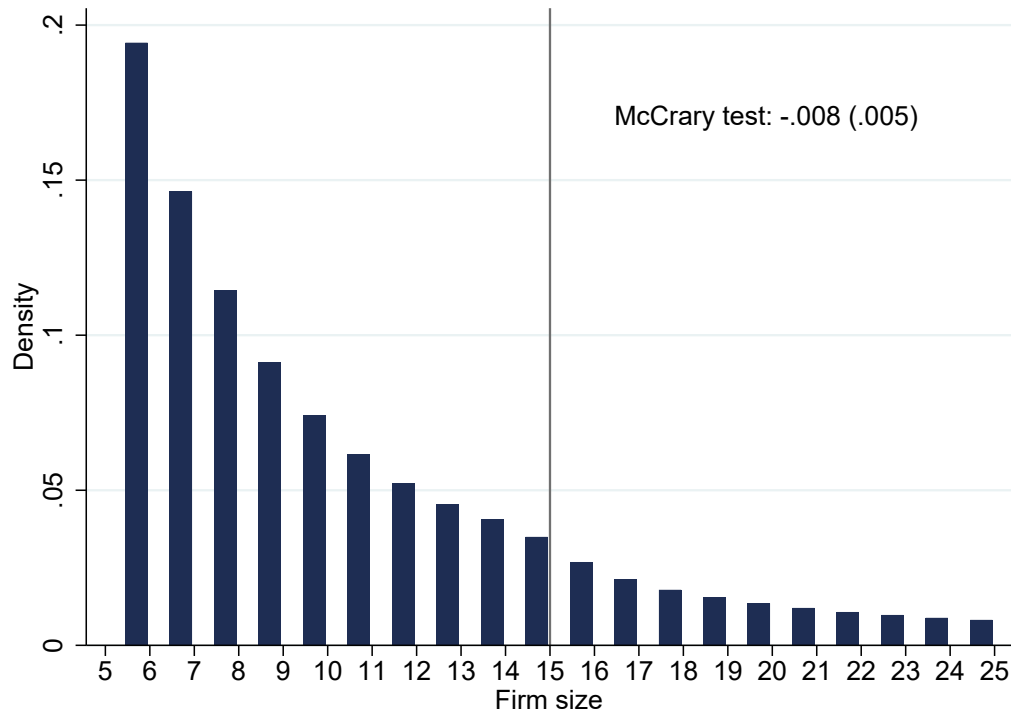
Notes: The graph shows the probability density function of FTE firm size by 1-unit bins for the years 2000-2015. The graph also reports the McCrary test statistics for the presence of a discontinuity in the probability density function of FTE size at 15 and its standard error. FTE firm size is defined as the full-time equivalent of all employees in the firm, including those who are not eligible for CIGS (managers, apprentices and work-from-home employees) and those who are currently on unpaid leave (unless the firm has hired a replacement). Part-time workers are counted in full-time equivalent units.

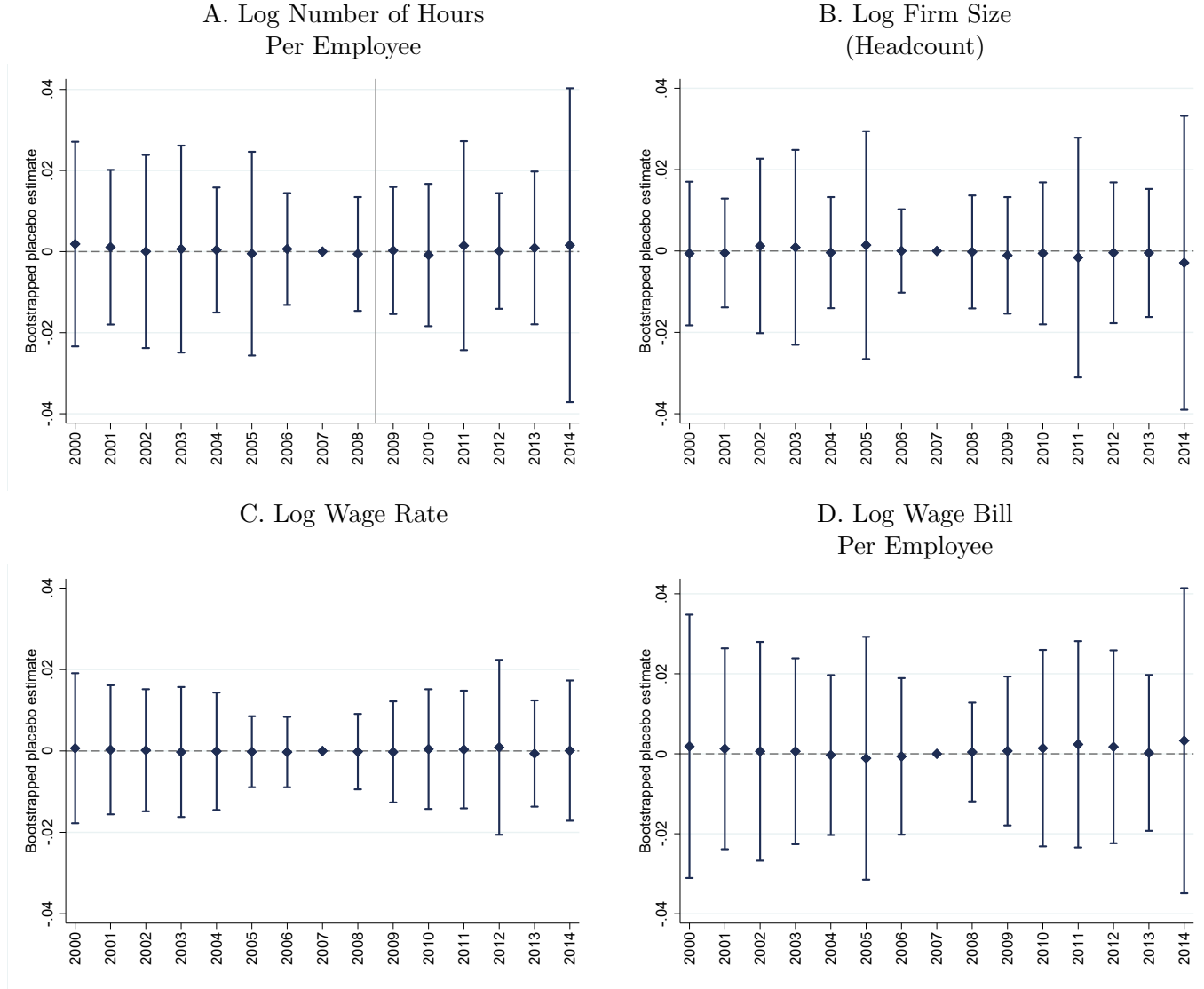Figure A-3: McCrary Test Statistic of Discontinuity in Firms' Size Distribution

A. Eligible INPS Codes

B. Non-Eligible INPS Codes

Notes: The graphs show the McCrary test statistic for the presence of a discontinuity in the probability density function of FTE size at 15 and its confidence interval for each year $t \in [2000, 2014]$, and for eligible and non-eligible INPS codes separately. The vertical bars indicate 95% confidence intervals. FTE firm size is defined as the full-time equivalent of all employees in the firm, including those who are not eligible for CIGS (managers, apprentices and work-from-home employees) and those who are currently on unpaid leave (unless the firm has hired a replacement). Part-time workers are counted in full-time equivalent units.

Figure A-4: Fraction of Firms Changing Eligibility Status Due to INPS Code Changes (2000-2014)
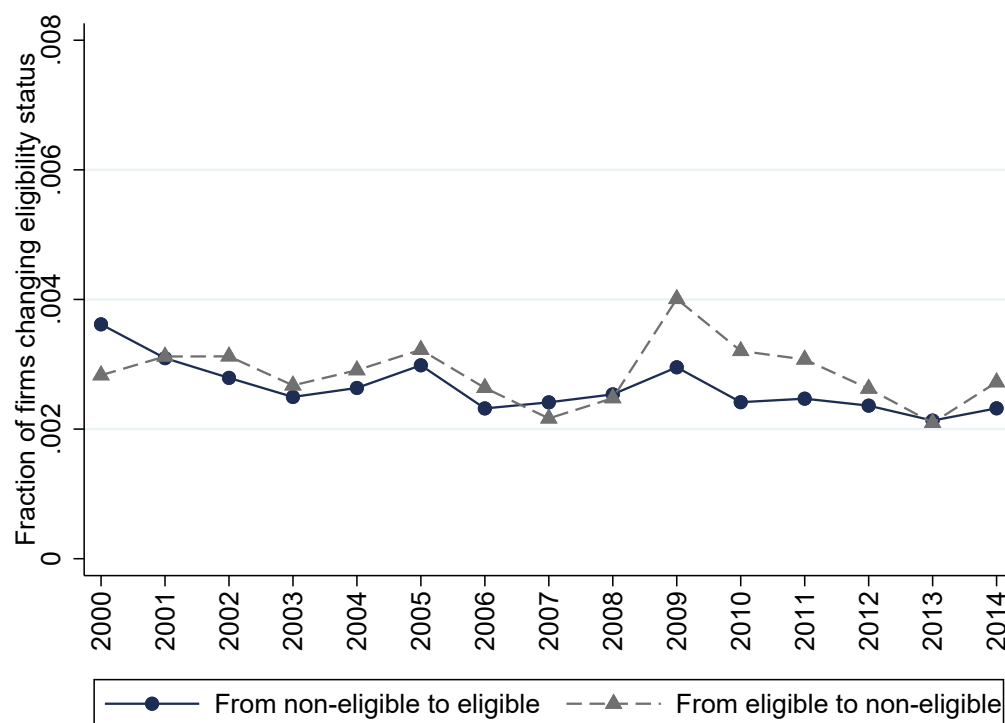
Notes: The graphs shows the fraction of firms that change eligibility status due to a change in their INPS code for each year $t \in [2000, 2014]$, and separately for firms changing their status from eligible to non-eligible and vice versa.

Figure A-5: Placebo Estimates of the Effects of Short Time Work on Firms' Outcomes

A. Log Number of Hours
Per Employee

B. Log Firm Size
(Headcount)

C. Log Wage Rate

D. Log Wage Bill
Per Employee

Notes: These graphs show the coefficients $\hat{\gamma}_1^t$ estimated from a placebo version of equation 1 for all years $t \in [2000, 2014]$ for different firm-level outcomes. Restricting the sample to non-eligible INPS codes, we select a random series of INPS codes to which we assign a placebo "eligible" status. On this sample we run specification 1. The omitted year is 2007, so all results are relative to 2007. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors from 100 replications of the placebo estimation. The wage rate is defined as total earnings per week worked per employee.

Figure A-6: P-Values of Permutation Test on Baseline Estimates Using Bootstrapped Placebo Estimates

A. Log Number of Hours
Per Employee

B. Log Firm Size
(Headcount)

C. Log Wage Rate

D. Wage Bill
Per Employee
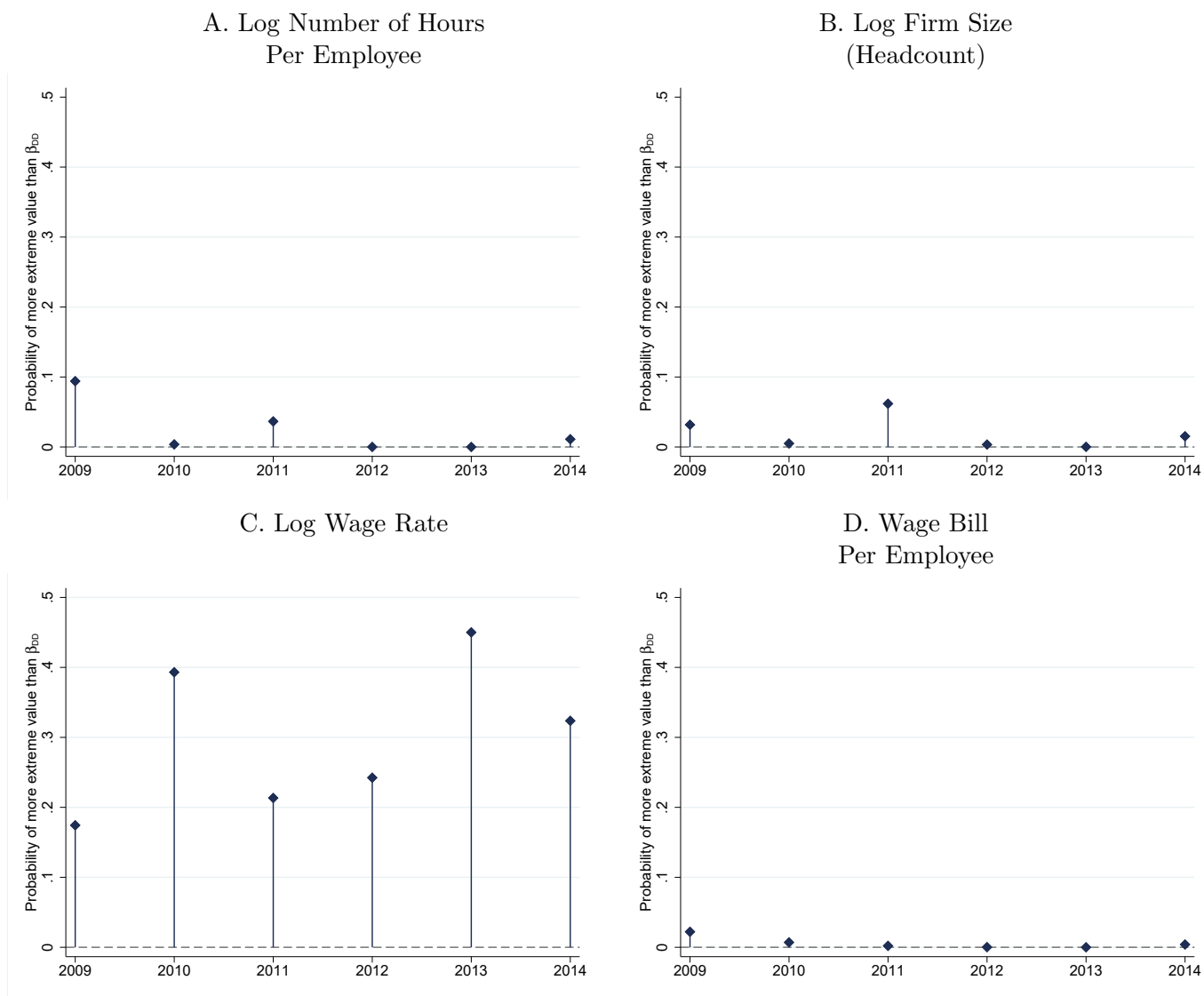
Notes: These graphs report the p-values of a test of equality of the baseline reduced-form estimates of model 1 reported in Figure 2 and the bootstrapped placebo estimates reported in Figure A-5 for the years 2009 to 2014. The p-values indicate the probability of randomly estimating an effect at least as large as our baseline estimates. The wage rate is defined as total earnings per week worked per employee.

Appendix B: Dynamic Treatment Effects

B.1 Recursive Identification of Dynamic Treatment Effects for Firms' Outcomes

To identify the full sequence of dynamic effects of STW treatment, we develop a methodology similar in spirit to the recursive identification of dynamic treatment effects in Cellini, Ferreira and Rothstein [2010]. We would like to identify the sequence of dynamic treatment effects $\{\beta_0^{TOT}, \beta_1^{TOT}, ..., \beta_k^{TOT}\}$ which capture the effect of receiving STW treatment on outcome in the year of treatment (β_0^{TOT}), one year after treatment (β_1^{TOT}), etc., up to k years after treatment (β_k^{TOT}). We focus our sample on all firms that are active in 2009, and with FTE firm size between 5 and 25 workers in 2008. We create the instrumental variable Z_{2009}, equal to one if a firm is eligible to STW in 2009, that is equal to the triple interaction of being above the 15 FTE firm size threshold in 2008 and being in an eligible INPS code in 2009. We know that this variable will be correlated with the probability of STW treatment in 2009 (T_{2009}), but also with the probability of treatment in 2010 (T_{2010}), in 2011 (T_{2010}), etc. We also know from Appendix Figure B-3 that Z_{2009} is not correlated with treatment in the past (T_{2008}, T_{2007}, etc.). If we now run on this sample the following reduced-form regression:

$$
\begin{aligned}
Y_{igst} = & \sum_j \beta_j^{RF} \cdot Z_{2009} \cdot \mathbb{1}[j = t] \\
& + \sum_j \sum_k \gamma_2^{jk} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] * \mathbb{1}[k = s] * \mathbb{1}[j = t] \right\} \\
& + \sum_j \sum_k \gamma_3^{jk} \cdot \left\{ \mathbb{1}[k = s] * \mathbb{1}[N_{i,t-1} > 15] * \mathbb{1}[j = t] \right\} \\
& + \sum_j \sum_k \gamma_4^{jk} \cdot \left\{ \mathbb{1}[k = s] * \mathbb{1}[j = t] \right\} \\
& + \sum_k \gamma_5^{k} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] * \mathbb{1}[k = s] * \mathbb{1}[N_{i,t-1} > 15] \right\} \\
& + \sum_k \gamma_6^{k} \cdot \left\{ \mathbb{1}[g \in \mathcal{E}] * \mathbb{1}[k = s] \right\} + v_{igst}
\end{aligned}
\tag{13}
$$

of the baseline IV model (see equations (3) in appendix) using Z_{2009} as an instrument, the estimated coefficients of the reduced form for each year 2009, 2010, etc. ($\beta_{2009}^{RF}, \beta_{2010}^{RF}$, etc.) capture the dynamic Intention-To-Treat (ITT) effects from in 2009, letting potential future treatment occur.

$$
\beta_{2009}^{RF} = \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}}
\tag{14}
$$

$$
\beta_{2010}^{RF} = \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2010}}{\mathrm{d}Z_{2009}} + \beta_1^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}}
\tag{15}
$$

The first stage regressions of T_{igst} on Z_{2009} enable us to identify $\frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}}, \frac{\mathrm{d}T_{2010}}{\mathrm{d}Z_{2009}}$, etc. Using these estimates, the estimates of the ITT effects $\hat{\beta}_t^{RF}$ and the recursive structure of equations (14), (15), etc., we can identify the sequence of dynamic treatment effects $\{\beta_0^{TOT}, \beta_1^{TOT}, ..., \beta_k^{TOT}\}$.

We display in Figure B-2 the results of these dynamic TOT effects, for various outcomes. The results suggest that the effects are large on impact, but disappear immediately once treatment stops.

Figure B-1: Effect of INPS code and firm size eligibility interaction on the probability of having received short time work treatment in the past 5 years
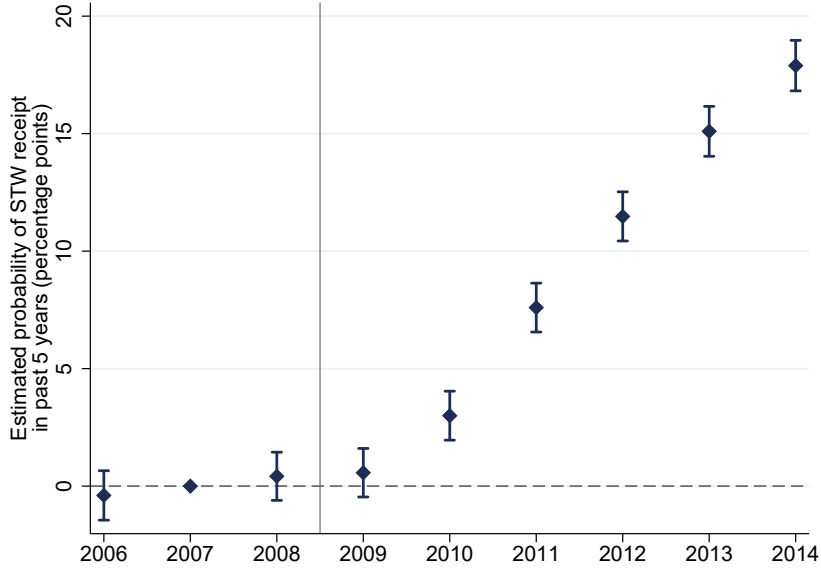
Notes: The graph shows the coefficients $\hat{\gamma}_1^t$ estimated from equation 1 for all years $t \in [2006, 2014]$ using as an outcome the probability of having received STW in the previous five years. The probability of STW receipt in the previous 5 years is at the firm level. The omitted year is 2007, so all results are relative to 2007. The vertical bars indicate 95% confidence intervals based on cluster-robust standard errors.

B.2 Identification of Dynamic Treatment Effects for Workers
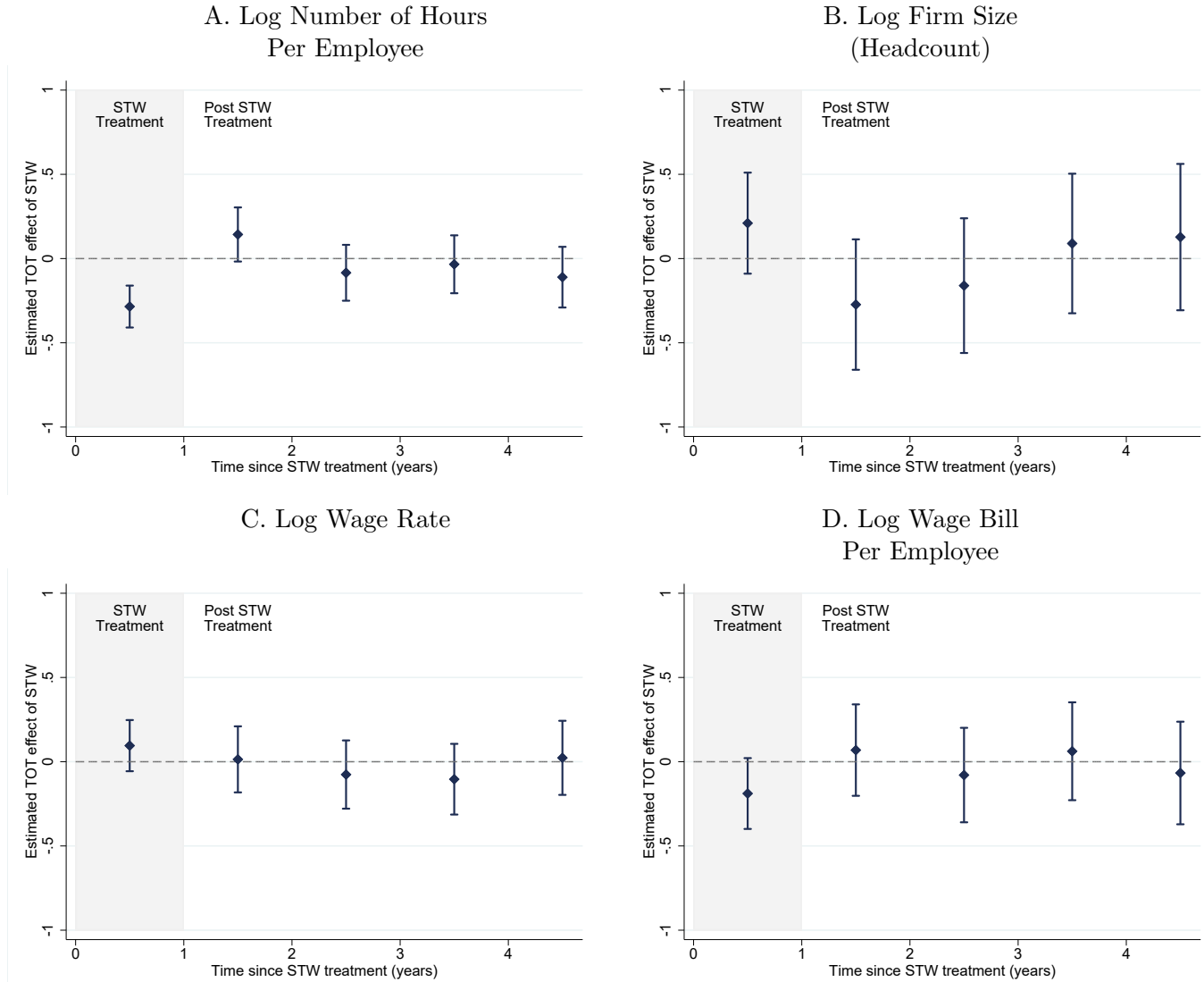
We want to understand to what extent the interesting dynamic patterns from the previous event studies reveal the deeper causal dynamic impact of STW treatment. Endogeneity concerns prevent interpreting the event study estimates on the treated as the causal dynamic impact of short time work. The incidence and timing of CIGS treatment across firms are indeed not random and workers within these firms may differ from other workers along various characteristics affecting their labor market dynamics. We start by explaining these issues, and show how two things can be done to tackle this issue.

Model:　We start by formulating a general statistical model of the dynamics of workers outcomes:

$$Y_{i,j,t+k} = \eta_i + X'_{it}\alpha_k + \beta_k \mathbb{1}[T_{jt} = 1] + \varepsilon_{j,t+k} + \mu_{i,t+k}$$

where $Y_{i,j,t+k}$ is the outcome of worker i in year $t+k$, given the worker was in firm j at time t.

Figure B-2: TOT Estimates of the Dynamic Effects of Short Time Work

A. Log Number of Hours
Per Employee

B. Log Firm Size
(Headcount)

C. Log Wage Rate

D. Log Wage Bill
Per Employee

Notes: The graphs report the coefficients $\hat{\beta_k^{TOT}}$ for $k \in [0, ..., 4]$ estimated recursively as illustrated in Appendix A.2. The β_k^{TOT} identify dynamic treatment effects of STW receipt at time $k = 0$ on outcomes at time $k \in [0, ..., 4]$. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. The wage rate is defined as total earnings per hour worked per employee.

This outcome depends on some observed and unobserved individual characteristics η_i and X_{it}, on having received STW treatment or not at time t. This outcome also depends on the dynamics of two types of unobserved shocks: firm level shocks $\varepsilon_{j,t+k}$ and individual level shocks $\mu_{i,t+k}$.

To identify the sequence of dynamic effects of STW β_k, we first need to control for individual fixed effects η_i: this is easily done using individual fixed effect panel models. Second, we need to control for individual level characteristics of workers X, as they may affect dynamics of labor market: this is done creating proper control groups using nearest-neighbor matching.

The next important concern is that firms who select into STW in t are subject to (unobservable) bad shocks in t ($\varepsilon_{j,t}$), that are possibly quite time persistent, creating a correlation between STW treatment and $\varepsilon_{j,t+k}$. In other words, workers treated by STW will do bad because the firms that trigger STW experience bad shocks. A final issue is the potential correlation between $\mathbb{1}[T_{jt} = 1]$ and $\mu_{i,t+k}$.

A first simple way to address these two concerns is to create counterfactual event studies that put bounds on the values of these firm and individual shocks, and therefore bounds on the treatment effects of STW. Another approach is to use our instrument for STW treatment T_{jt}, based on the interaction between firm size and INPS codes.

Bounds on Dynamic Treatment Effects Using Counterfactual Event Studies   The idea here is to use comparison groups as bounds on the distribution of the unobserved shocks, and therefore bound causal effect of STW.

Intuitively, treated workers at time t are selected on the basis that the firm in which they are employed experiences a negative (unobservable) shock in t.

Counterfactual 1: Similar worker at time $t - 1$ from any non eligible firms due to firm size and INPS code. Because only the worse shocks select into STW, the outcomes for workers in this comparison group can be thought of as an upper bound counterfactual for what would have happened to treated workers in the absence of the program. And the comparison between the event study estimates for treated workers and workers of this first comparison group provide therefore a lower bound estimate on the dynamic treatment effect of STW.

Counterfactual 2: Similar worker at time $t - 1$ from non eligible firms due to firm size and INPS code that experience mass layoff in t. We assume that the shock triggering mass layoff is at least as bad as STW shock and that the firms would have used STW instead if they were eligible. As we show in section 5.1, not all firms who take up STW would have been laying off workers. In that sense, the layoff comparison group is clearly more negatively selected than our treated group. Under this assumption, workers in this mass layoff comparison group can be thought as a lower bound counterfactual for what would have happened to treated workers absent STW. And the comparison between the event study estimates for treated workers and workers of this second comparison group provides an upper bound estimate of the effect of STW.

IV-based Recursive Identification   We can also get a causal estimate of the dynamic effect of STW on workers by implementing a version of our IV recursive identification method used in

section 3.4, but focusing on workers outcomes instead of firms. The methodology relies on using the interaction between firm size and INPS code of the firm in which the worker is working in 2008 as an instrument for STW treatment (using the the same controls as in our baseline IV for firms). The intuition for identification is similar to the one in section 3.4. Working in an eligible firm in 2008 (Z_{2008}) is an instrument for being treated in 2009. The reduced form regression of outcomes in 2009 on the instrument identifies the contemporaneous effect of STW treatment in 2009. But our instrument Z_{2008} is also correlated with treatment in 2010. The reduced form regression of outcomes in 2010 on the instrument identifies both the one year lagged effect of treatment in 2009 and the contemporaneous effect of treatment in 2010. And so on and so forth. Exploiting this recursive structure, we can back out the dynamic TOT effects of STW on workers outcomes. While this approach has the advantage of identifying the causal dynamic effect of STW on workers, one drawback is that, given the recursive structure of estimates, standard errors are quite large.

Results In Figure B-3, we overlay the upper bound and lower bound estimates from the event study approach with the IV-based TOT estimate of the dynamic effect of STW treatment. In panel A, we show the effect for employment, and in panel B the effect on worker's total gross earnings plus transfers. The graph shows that in both cases, the upper bound estimate, which compares treated workers to their layoff counterfactual, is positive at the time of treatment (event year 0), but quickly converges to being close to zero, as suggested by the event studies in Figure 4. The point estimates for the TOT effects are interestingly extremely close to these upper bound estimates, although more imprecisely estimated.

Overall, these results confirm that STW has a positive effect on workers outcomes during treatment and therefore provides short term insurance to workers in firms exposed to shocks. Yet, these effects entirely disappear after treatment when looking at total earnings and transfers, so that STW provides no longer term insurance to workers. In other words, there was no long term beneficial effect of keeping treated workers in firms treated by CIGS during the Great Recession in Italy. This also suggests that there is limited scope for experience effects in the CIGS context, which confirms a stream of evidence on the absence of significant returns to experience for workers treated by active labor market programs .

Figure B-3: Dynamic Effects of STW on Workers' Outcomes:

A. Probability of Employment
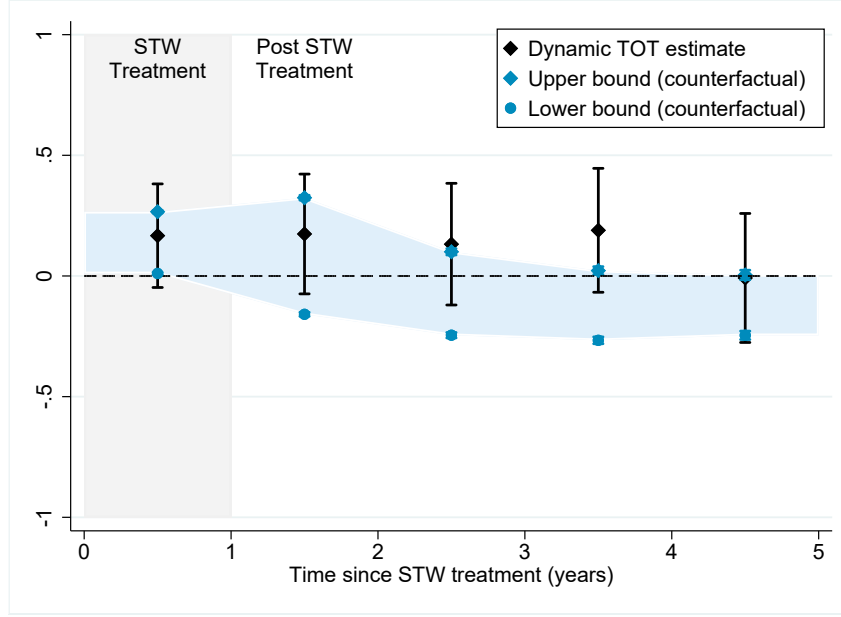
B. Earnings + CIGS/Transfers
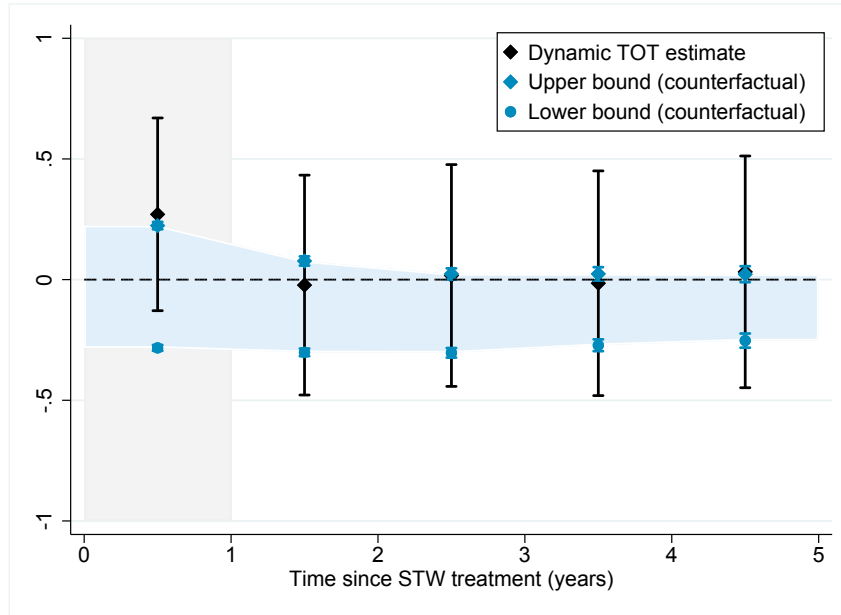
Notes: The graphs report TOT estimates of the dynamic treatment effect of STW receipt on workers' employment probability and total earnings including social insurance transfers and STW. The coefficients $\beta_k^{\hat{TOT}}$ (indicated by darker solid diamonds) for $k \in [0, ..., 4]$ and are estimated recursively as illustrated in Appendix A.2. The β_k^{TOT} identify dynamic treatment effects of STW receipt at time $k = 0$ on outcomes at time $k \in [0, ..., 4]$. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. The shaded area shows upper- and lower-bound estimates of the dynamic effect from the event study graphs reported in Figure 4. The upper bound (indicated by lighter solid diamonds) compares treated individuals with the layoff counterfactual. The lower bound (indicated by lighter circles) compares treated workers with workers in non-eligible firms.

Appendix C: Selection & Spillover Effects - Additional Evidence

Figure C-1: FRACTION OF WORKERS TREATED BY CIGS ACROSS ITALIAN LOCAL LABOR MARKETS (2010-2013)
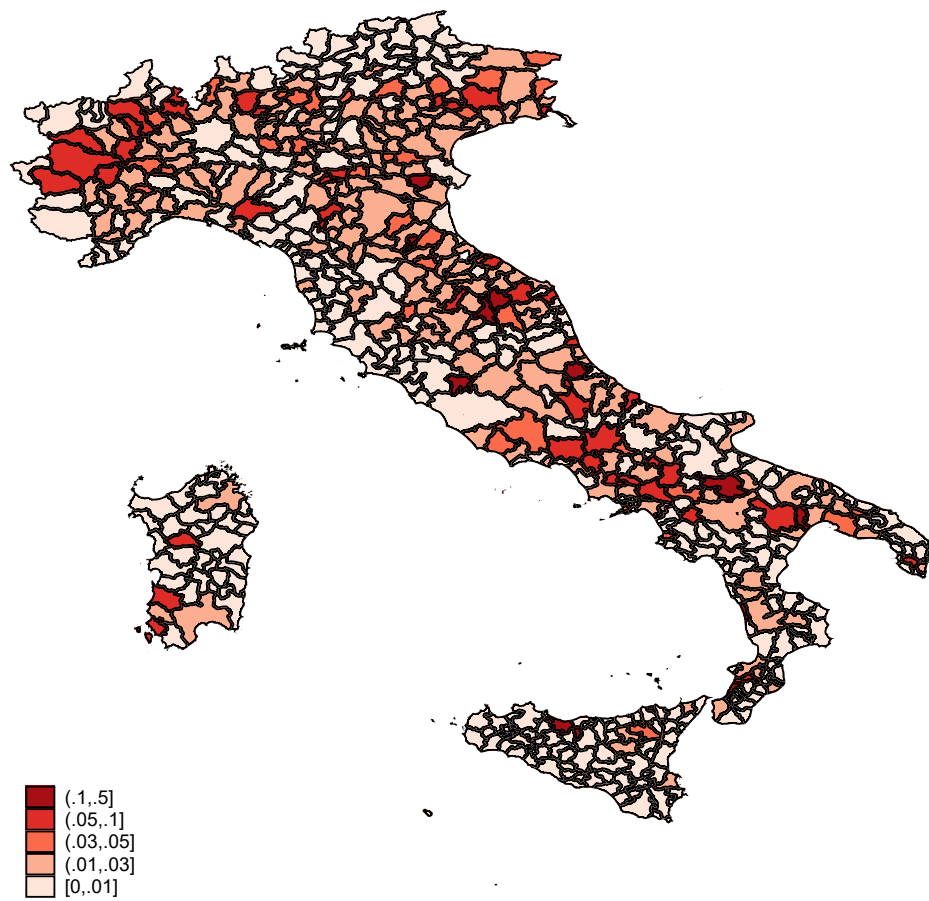
Notes: The graph shows a map of the Italian territory subdivided into 611 local labor markets (LLM), as defined by the Italian Statistical Institute (ISTAT). The graph reports the fraction of workers treated by CIGS in the years 2010 to 2013 by LLM. The fraction of treated workers is defined as the number of workers with at least one STW spell divided by the total number of employees in the LLM.

Figure C-2: FRACTION OF WORKERS ELIGIBLE TO CIGS IN A LLM BASED ON FIRM SIZE AND INPS CODES DURING THE PRE-RECESSION PERIOD VS FRACTION OF WORKERS ON CIGS DURING THE RECESSION
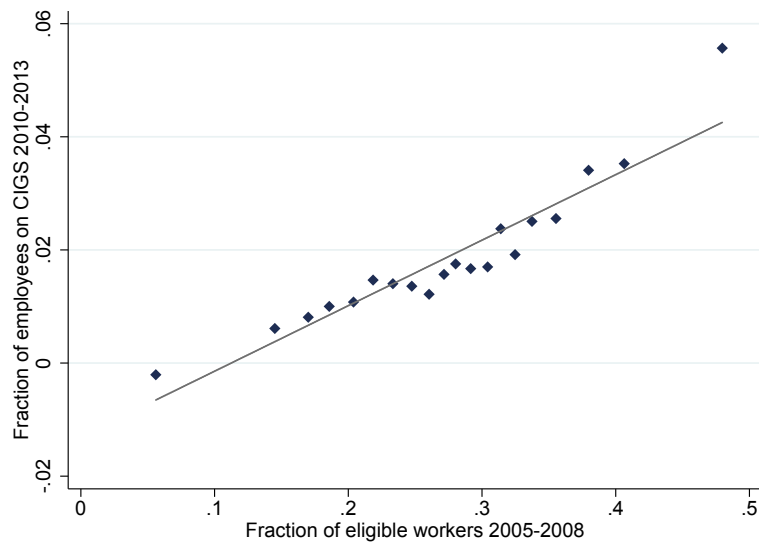
Notes: The graph reports a binned scatterplot of the relationship between the fraction of employees on STW in 2010-2013 and the fraction of workers eligible to STW in 2005-2008 at the local labor market level based on the interaction between firm size and INPS codes. Both variables are residualized on firm level and LLM level controls (see text for details). This relationship corresponds to the first stage of the IV model in equation 7.

Appendix D: Model - Details and Further Results

D.1 Firm's problem

Firms faces productivity shocks ϵ_t. The firm receives profits, Π, given their production function F and productivity, less labour and hiring costs. There is exogenous separation at rate δ, and hiring costs c. The firms vacancy filling probability is $q(\theta_t)$. Firms discount the future at the same rate β as workers.

Firms determine every period the number of vacancies to be posted v_t to maximize profits:

$$\Pi(\epsilon_t, n_{t-1}) = \max_{v_t}\{\epsilon_t F(h_t, n_t) - w h_t n_t - c v_t + \beta \mathbb{E}_t[\Pi(\epsilon_{t+1}, n_t)]\} \tag{16}$$

subject to the law of motion of employment:

$$n_t = (1 - \delta) \cdot n_{t-1} + q(\theta_t) \cdot v_t \tag{17}$$

The first order condition of profit maximization implicitly determines the demand for employment $n_t = n(\theta_t, h_t, w)$ of the firm.

$$\{\mathbf{n}\}\ \epsilon_t F'_n(h_t, n_t) = w h_t + \frac{c}{q(\theta_t)} - \beta E_t(\Pi_n(\epsilon_{t+1}, n_t)) \tag{18}$$

Given the firm's envelope condition:

$$\Pi'_n(\epsilon_{t+1}, n_t) = (1 - \delta)\frac{c}{q(\theta_{t+1})} \tag{19}$$

Therefore the FOC with respect to n, equation (18), becomes:

$$\epsilon_t F'_n(h_t, n_t) = w h_t + \frac{c}{q(\theta_t)} - \beta(1 - \delta)\mathbb{E}_t(\frac{c}{q(\theta_{t+1})}) \tag{20}$$

In a stationary equilibrium, $\theta_t = \theta_{t+1} = \theta$, equation (20) reduces to:

$$\epsilon_t F'_n(h_t, n_t) = w h_t + (1 - \beta(1 - \delta))\frac{c}{q(\theta)} \tag{21}$$

D.2 Characterization of hours schedule & employment responses to STW

Optimal employment is determined by FOC (21) above of maximization of total profits w.r.t, to vacancies. This determines employment as a function of hours, wages, and tightness.

Workers and firms bargain over the surplus created by realized matches, which translates into an hours schedule and a wage schedule. When firms and workers bargain over hours and wages there are a large number of general hours and wage schedules: $h(w, \theta, \epsilon, n, b, \tau, t)$ and $w(h, \theta, \epsilon, n, b, \tau, t)$ that solutions because hours and wages are imperfect substitutes in both sides' objective functions.

But since each side receives a share of the overall surplus, given an agreed wage, the level of agreed hours must maximize the shared surplus. Note that this does not coincide with Nash's Pareto efficiency axiom for a bargaining solution because it may be possible to make both sides better off with a different wage and hours schedule. But if wages are determined by some form of rigid rule, which corresponds to most wage bargaining setting, then such an hours solution seems plausible. In practice, in Italy, wage are negotiated by industry-wide bargaining over fixed period of time (of approximately three year).

Given a particular fixed wage rule $w(h, \theta, \epsilon, n, b, \tau, t)$ we can now characterize hours schedule conditional on this particular wage schedule.

To see how the implied hours schedule behaves when it is determined in this manner, we first reanalyze the worker continuation values,

$$
\begin{aligned}
W_H =& u(c_H, h_H) + \beta[\delta W_U + (1 - \delta)W_H], \\
W_L =& u(c_L, h_L) + \beta[\delta W_U + (1 - \delta)W_L], \\
W_U =& u(c_U, 0) + \beta[(1 - \phi(\theta))W_U + \phi(\theta)\{\rho W_H + (1 - \rho)W_L\}].
\end{aligned}
$$

Referring to W_H, W_L, and W_U as unknowns; we have three equations and three unknowns. Let us solve out for the unknowns,

$$
\begin{aligned}
W_H =& \frac{F(\theta)}{1 - \beta(1 - \delta)}\left[\beta\delta u(c_U, h_U) + \left\{1 + \frac{\beta^2\delta\phi(\theta)\rho}{1 - \beta(1 - \delta)}\right\}u(c_H, h_H) + \frac{\beta^2\delta\phi(\theta)(1 - \rho)}{1 - \beta(1 - \delta)}u(c_L, h_L)\right], \\
W_L =& \frac{F(\theta)}{1 - \beta(1 - \delta)}\left[\beta\delta u(c_U, h_U) + \frac{\beta^2\delta\phi(\theta)\rho}{1 - \beta(1 - \delta)}u(c_H, h_H) + \left\{1 + \frac{\beta^2\delta\phi(\theta)(1 - \rho)}{1 - \beta(1 - \delta)}\right\}u(c_L, h_L)\right], \\
W_U =& F(\theta)\left[u(c_U, h_U) + \frac{\beta\phi(\theta)\rho}{1 - \beta(1 - \delta)}u(c_H, h_H) + \frac{\beta\phi(\theta)(1 - \rho)}{1 - \beta(1 - \delta)}u(c_L, h_L)\right],
\end{aligned}
$$

where $F(\theta) = \frac{1 - \beta(1 - \delta)}{(1 - \beta(1 - \phi(\theta)))(1 - \beta(1 - \delta)) - \beta^2\delta\phi(\theta)}$. So the continuation values are a convex combination of instantaneous utility from different states, where the weighting depends on an endogenous variables - labor market tightness. Using previous notation, we can represent this in matrix form,

$$
W = \Lambda'U,
$$

where $W = [W_H, W_L, W_U]'$ and $U = [u(c_H, h_H), u(c_L, h_L), u(c_U, h_U)]'$. From this, we can see that,

$$W_i - W_U = \frac{(1 - \beta\phi(\theta))u(c_i, h_i) - (1 - \beta)u(c_u, 0)}{1 - \beta(1 - \delta - \phi(\theta))},$$

$$\Rightarrow \frac{d(W_i - W_U)}{dh_i} = (1 - \beta(1 - \delta - \phi(\theta)))^{-2} \Bigg\{ [1 - \beta(1 - \delta - \phi(\theta))] \dots$$

$$\dots \left[(1 - \beta\phi(\theta))(w_i(1 - \tau_i)u_c(c_i, h_i) + u_h(c_i, h_i)) - \beta u(c_i, h_i)\frac{d\phi(\theta)}{dh_i} \right] \dots$$

$$\dots - [(1 - \beta\phi(\theta))u(c_i, h_i) - (1 - \beta)u(c_u, 0)]\beta\frac{d\phi(\theta)}{dh_i} \Bigg\}.$$

Since the agents considering the bargaining process are atomistic relative to the total size of the economy, we can ignore general equilibrium effects on market tightness,

$$\frac{d(W_i - W_U)}{dh_i} = \eta(\theta)[w_i(1 - \tau_i)u_c(c_i, h_i) + u_h(c_i, h_i)],$$

$$\Rightarrow \frac{d^2(W_i - W_U)}{dh_i^2} = \eta(\theta)[w_i^2(1 - \tau_i)^2 u_{cc}(c_i, h_i) + u_{hh}(c_i, h_i)],$$

$$\Rightarrow \frac{d^2(W_L - W_U)}{dh_L d\tau} = \eta(\theta)\left[-w_L u_c(c_L, h_L) - w_L^2(1 - \tau_L)h_L u_{cc}(c_L, h_L) + \frac{dh_L}{d\tau_L}u_{hh}(c_L, h_L) \right],$$

$$\Rightarrow \frac{d^2(W_H - W_U)}{dh_H d\tau} = 0,$$

$$\Rightarrow \frac{d^2(W_i - W_U)}{dh_i d\varepsilon_i} = \eta(\theta)\left[\frac{dw_i}{d\varepsilon_i}(1 - \tau_i)u_c(c_i, h_i) \dots \right.$$

$$\left. \dots + w_i(1 - \tau_i)\left[\frac{dw_i}{d\varepsilon_i}(1 - \tau_i)h + w(1 - \tau)\frac{dh_i}{d\varepsilon_i} \right]u_{cc}(c_i, h_i) + \frac{dh_i}{d\varepsilon_i}u_{hh}(c_i, h_i) \right],$$

where $\eta(\theta) = \frac{1 - \beta\phi(\theta)}{1 - \beta(1 - \delta - \phi(\theta))}$ and we assume separability in hours and consumption. Therefore, assuming as a benchmark that a worker is on their neoclassical intratemporal first order condition, the difference $W_i - W_U$ increases with h_i if the probability of finding a job decreases in h_i. The surplus for a match between a worker and a level i productivity firm is,

$$S_i = W_i - W_U + \varepsilon_i F_n(h_i, n_i) - w_i h_i.$$

As explained above, for a given wage schedule this should be maximized with respect to h_i

$$\frac{dS_i}{dh_i} = \frac{d(W_i - W_U)}{dh_i} + \varepsilon_i F_{nh}(h_i, n_i) + \varepsilon_i F_{nn}(h_i, n_i)\frac{dn_i}{dh_i} - w_i - h_i\frac{dw_i}{dh_i} = 0.$$

This equation implicitly determines a level of hours, so given a unique solution we can do comparative statics. Firstly, looking at the STW the τ parameter, and assuming that all third

derivatives of the production function are negligibly small, we have,

$$\frac{dh_i}{d\tau} = \frac{-\left[\frac{d^2(W_i - W_U)}{dh_i d\tau} + \varepsilon_i F_{nn}(h_i, n_i)\frac{d^2 n_i}{dh_i d\tau}\right]}{\frac{d^2(W_i - W_U)}{dh_i^2} + \varepsilon_i F_{nn}(h_i, n_i)\frac{d^2 n_i}{dh_i^2}}.$$

Now looking at the productivity parameter ε_i, we find:

$$\frac{dh_i}{d\varepsilon_i} = \frac{-\left[\frac{d^2(W_i - W_U)}{dh_i d\varepsilon_i} + F_{nh}(h_i, n_i) + F_{nn}(h_i, n_i)\frac{dn_i}{dh_i} + \varepsilon_i F_{nn}(h_i, n_i)\frac{d^2 n_i}{dh_i d\varepsilon_i} - \frac{dw_i}{d\varepsilon_i}\right]}{\frac{d^2(W_i - W_U)}{dh_i^2} + \varepsilon_i F_{nn}(h_i, n_i)\frac{d^2 n_i}{dh_i^2}}.$$

To look at the reaction of employment to different variables we take the firms first order condition for employment,

$$A_i[\varepsilon_i F_n(h_i, n_i) - w_i h_i] = \frac{1}{q(\theta)},$$

where $A_H = \frac{\rho(1 - \beta(1 - \delta))}{c_v}$ and $A_L = \frac{(1 - \rho)(1 - \beta(1 - \delta))}{c_v}$. So total differentiation gives us,

$$\frac{dn_i}{dh_i} = \frac{w_i - \varepsilon_i F_{nh}(h_i, n_i)}{\varepsilon_i F_{nn}(h_i, n_i)},$$

where we use the fact that firms do not internalize their impact on market tightness and wages do not change in response to hours. Assuming third derivatives of the production function equal zero and wages do not move in response to τ,

$$\frac{d^2 n_i}{dh_i^2} = 0,$$

$$\frac{d^2 n_i}{dh_i d\tau} = 0,$$

$$\frac{d^2 n_i}{dh_i d\varepsilon_i} = \frac{\left[\frac{dw_i}{d\varepsilon_i} - F_{nh}(h_i, n_i)\right]\varepsilon_i F_{nn}(h_i, n_i) - F_{nn}(h_i, n_i)[w_i - \varepsilon_i F_{nh}(h_i, n_i)]}{[\varepsilon_i F_{nn}(h_i, n_i)]^2}.$$

Combining this with our expressions for $\frac{dh_i}{d\varepsilon_i}$ and $\frac{dh_i}{d\varepsilon_i}$, where we have assumed third derivatives of the production function equal zero,

$$
\frac{dh_i}{d\tau} = \frac{-\left[\frac{d^2(W_i - W_U)}{dh_i d\tau}\right]}{\frac{d^2(W_i - W_U)}{dh_i^2}} = \frac{w_i u_c(c_i, h_i) + w_i^2(1 - \tau_i) h_i u_{cc}(c_i, h_i)}{w_i^2(1 - \tau_i)^2 u_{cc}(c_i, h_i) + 2u_{hh}(c_i, h_i)},
$$

$$
= \frac{h_i(\sigma_i - 1)/(1 - \tau_i)}{\sigma_i + 2\gamma_i \kappa_i},
$$

$$
\frac{dh_i}{d\varepsilon_i} = \frac{-\left[\frac{d^2(W_i - W_U)}{dh_i d\varepsilon_i} + F_{nh}(h_i, n_i) + F_{nn}(h_i, n_i)\frac{dn_i}{dh_i} + \varepsilon_i F_{nn}(h_i, n_i)\frac{d^2 n_i}{dh_i d\varepsilon_i} - \frac{dw_i}{d\varepsilon_i}\right]}{\frac{d^2(W_i - W_U)}{dh_i^2}},
$$

$$
= \frac{-\eta(\theta)\frac{dw_i}{d\varepsilon_i}(1 - \tau_i)\left(u_c(c_i, h_i) + w_i(1 - \tau_i)h_i u_{cc}(c_i, h_i)\right)}{2\eta(\theta)[w_i^2(1 - \tau_i)^2 u_{cc}(c_i, h_i) + u_{hh}(c_i, h_i)]},
$$

$$
= \frac{-\epsilon_{w,\varepsilon} h_i(\sigma_i - 1)}{2\varepsilon_i[\sigma_i + \gamma_i \kappa_i]},
$$

where $\sigma_i = -\frac{w_i(1-\tau_i)h_i u_{cc}(c_i,h_i)}{u_c(c_i,h_i)}$, $\gamma_i = \frac{h_i u_{hh}(c_i,h_i)}{u_h(c_i,h_i)}$, $\kappa_i = \frac{-u_h(c_i,h_i)}{w_i(1-\tau_i)u_c(c_i,h_i)}$ and $\epsilon_{w,\varepsilon} = \frac{dw_i/w_i}{d\varepsilon_i/\varepsilon_i}$.

D.3 Equilibrium & Spillover Effects

A steady state equilibrium consists in a set of: (i) hours schedules h and wage schedules w that split the surplus in high and in low productivity firms subject to the incentive constraint that $W_k^e - W^u \geq 0$; (ii) labor demand functions n^d in high and in low productivity firms that maximizes firms' profits and (iii) a labor market tightness θ that clears the labor market subject to the steady state equality of flows in and out of employment. We borrow the equilibrium representation of Michaillat [2012]. A graphical illustration, using the calibrated version of our model, is presented in Figure D-1 below.

In this representation, the steady state equality of flows in and out of employment characterizes a labor supply $n^s(\theta, \delta)$, which is an increasing function of θ in the $\{n, \theta\}$ space. The profit maximization of firms determines a labor demand supply $n^d(\theta)$, which will be a decreasing function of θ when the marginal product of n is decreasing, and horizontal otherwise (panel A). With random matching, aggregate labor demand is simply the weighted sum of demands of high and low productivity firms. Equilibrium thightness and equilibrium employment are determined at the intersection of aggregate demand and supply (panel B). When STW is introduced, labor demand of low productivity firms increases, especially so when tightness is low (and hiring is therefore cheap). This in turn increases aggregate demand, and equilibrium tightness (panel C). This increase in equilibrium tightness is the force driving our observed spillover effects in the data. It makes hiring more costly for all firms, and therefore reduces employment of firms non treated by STW. This equilibrium mechanism captures the negative reallocation effects of STW which distorts employment towards

low productivity firms rather than high productivity firms. Again, this effect will be stronger the more horizontal labor demands are (that is, the more linear technology is in n) (panel D).

Figure D-1: Equilibrium Representation & Spillover Effects of STW
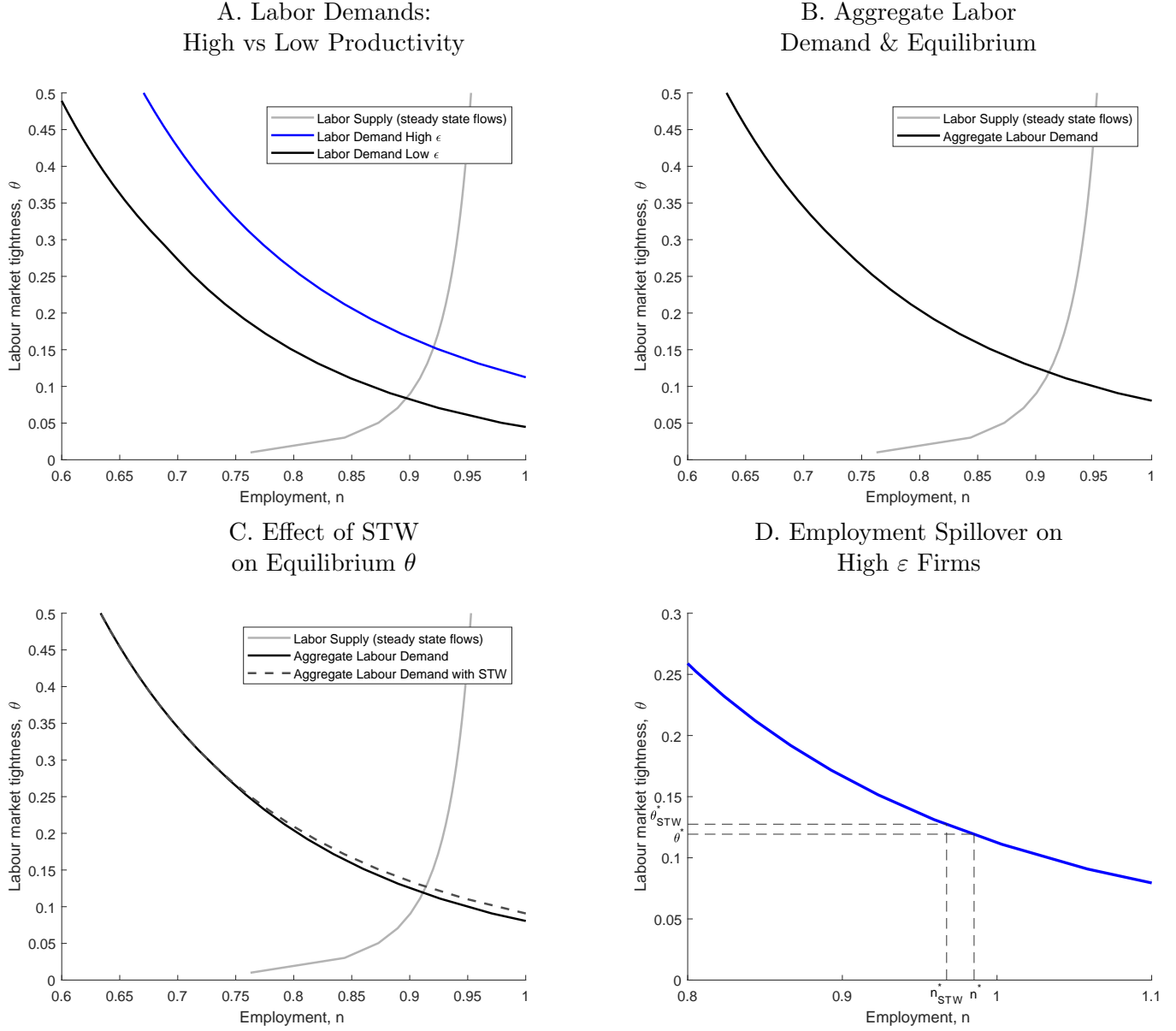
Notes: The Figure offers a graphical illustration of labor market equilibrium using the calibrated version of our model. In this representation, the steady state equality of flows in and out of employment characterizes a labor supply $n^s(\theta, \delta)$, which is an increasing function of θ in the $\{n, \theta\}$ space. The profit maximization of firms determines a labor demand supply $n^d(\theta)$, which will be a decreasing function of θ when the marginal product of n is decreasing, and horizontal otherwise (panel A). With random matching, aggregate labor demand is simply the weighted sum of demands of high and low productivity firms. Equilibrium thightness and equilibrium employment are determined at the intersection of aggregate demand and supply (panel B). When STW is introduced, labor demand of low productivity firms increases, especially so when tightness is low (and hiring is therefore cheap). This in turn increases aggregate demand, and equilibrium tightness (panel C). This increase in equilibrium tightness is the force driving our observed spillover effects in the data. It makes hiring more costly for all firms, and therefore reduces employment of firms non treated by STW. This equilibrium mechanism captures the negative reallocation effects of STW which distorts employment towards low productivity firms rather than high productivity firms. This effect will be stronger the more horizontal labor demands are (that is, the more linear technology is in n) (panel D).

Appendix E: Optimal STW Formula - Derivation & Calibration

E.1 Derivation of Proposition 1

The social planner problem is

$$\max_{\mathbb{T}} \ \mathcal{L}(\mathbb{T}) = t + \pi_H + \pi_L - Ub - \tau n_L w (1 - h_L) + \frac{1}{\mu} \Gamma(W_H, W_L, W_U, n_H, n_L)$$

$$\text{s.t } (1) \ (1 - \beta(1 - \delta))[\epsilon_H F_n(h_H, n_H) - w h_H] = \frac{c_v}{\rho q(\theta)},$$

$$(2) \ (1 - \beta(1 - \delta))[\epsilon_L F_n(h_L, n_L) - w h_L] = \frac{c_v}{(1 - \rho) q(\theta)},$$

$$(3) \ n = \frac{\phi(\theta)}{\delta + \phi(\theta)},$$

where $n = n_H + n_L$ and $U = 1 - n$.

Firstly, we focus on the social welfare effects,

$$\frac{1}{\mu n_L w (1 - h_L)} \left\{ \frac{d\Gamma(W_H, W_L, W_U, n_H, n_L)}{d\tau} \right\} = \frac{1}{\mu n_L w (1 - h_L)} \left\{ n_H \frac{dW_H}{d\tau} + n_L \frac{dW_L}{d\tau} + (1 - n) \frac{dW_U}{d\tau} \right. $$
$$\left. + \frac{dn_H}{d\tau} [W_H - W_U] + \frac{dn_L}{d\tau} [W_L - W_U] \right\}.$$

In a steady state equilibrium, $n_H = \rho n$ and $n_L = (1 - \rho) n$ so we can rewrite the above,

$$\frac{1}{\mu n_L w (1 - h_L)} \left\{ \frac{d\Gamma(W_H, W_L, W_U, n_H, n_L)}{d\tau} \right\} = \frac{1}{\mu n_L w (1 - h_L)} \left\{ n \left[\rho \frac{dW_H}{d\tau} + (1 - \rho) \frac{dW_L}{d\tau} \right] + (1 - n) \frac{dW_U}{d\tau} \right. $$
$$\left. + \frac{dn}{d\tau} \left[\rho W_H + (1 - \rho) W_L - W_U \right] \right\}.$$

In order to expand and interpret this equation we define a matrix,

$$\Lambda = \begin{bmatrix} \lambda_{H|H} & \lambda_{L|H} & \lambda_{U|H} \\ \lambda_{H|L} & \lambda_{L|L} & \lambda_{U|L} \\ \lambda_{H|U} & \lambda_{L|U} & \lambda_{U|U} \end{bmatrix} = [\Lambda_H : \Lambda_L : \Lambda_U]$$

$$= [1 - \beta(1 - \delta - \phi(\theta))]^{-1} \begin{bmatrix} 1 - \beta(1 - \rho\phi(\theta)) & \beta(1 - \rho)\phi(\theta) & \beta\delta \\ \beta\rho\phi(\theta) & 1 - \beta(1 - (1 - \rho)\phi(\theta)) & \beta\delta \\ \beta\phi(\theta)\rho & \beta\phi(\theta)(1 - \rho) & 1 - \beta(1 - \delta) \end{bmatrix}.$$

These new objects have a simple interpretation, $\lambda_{H|L}$ is the proportion of time spent employed in the high productivity firm over the lifetime of a worker who is currently employed in the low productivity firm. Similarly, $\lambda_{U|H}$ is the proportion of time spent unemployed over the lifetime of

a worker who is currently employed in the low productivity firm, and so on.

We define another vector to account for the proportions of employed - in the high and low productivity firms - and unemployed workers,

$$\mathcal{N} = \frac{1}{1-\beta} \begin{bmatrix} \rho n \\ (1-\rho)n \\ 1-n \end{bmatrix},$$

where the scalar multiplication will account for the fact that we are dealing with infinite streams of utility.

Lastly, we define the following scalars,

$$
\begin{aligned}
\Omega_i &= \mathcal{N}'\Lambda_i \qquad \text{for } i = H, L \\
\Delta &= \frac{\rho u(c_H, h_H) + (1-\rho)u(c_L, h_L) - u(c_U, 0)}{1 - \beta(1 - \delta - \phi(\theta))} \frac{1}{\mu}, \\
\Phi'(\theta) &= \phi'(\theta)\left[\frac{U}{\delta + \phi(\theta)} + \Omega_U\right], \\
E &= \tau n_L w(1 - h_L), \\
u_i^c &= \frac{du(c_i, h_i)}{dc} \qquad \text{for } i = H, L, \\
\mathbb{G}_i &= \frac{\Omega_i}{n_i}\frac{u_i^c}{\mu} \qquad \text{for } i = H, L
\end{aligned}
$$

where E is total expenditure on the policy. Δ is the weighted wedge in utility between being employed and unemployed. $\mathbb{G}_i$ is the adjusted marginal social welfare weights on either the employed in the low or high productivity firm. The adjustment comes from the $\frac{\Omega_i}{n_i}$ term, which accounts for the fact that individuals spend different amounts of time in the high or low productivity firm. If on average more time is spent in, say, the low productivity firm, then the social planner places greater weight on welfare in this state.

Now we can rewrite the original expression,

$$
\begin{aligned}
\frac{1}{\mu n_L w(1 - h_L)}\left\{\frac{d\Gamma(W_H, W_L, W_U, n_H, n_L)}{d\tau}\right\} = & \varepsilon_{h_H,\tau}\frac{n_H \cdot h_H\big[w - MRS_{c,h}^H\big]}{E}\mathbb{G}_H\frac{1-\rho}{\rho} + \\
& \varepsilon_{n_L \cdot h_L,\tau}\frac{h_L\big[w(1-\tau) - MRS_{c,h}^L\big]}{E}\mathbb{G}_L + \\
& \varepsilon_{\theta,\tau}\frac{\theta\Phi'(\theta)\Delta}{E} + \mathbb{G}_L .
\end{aligned}
$$

where $MRS_{c,h}^i = \frac{u_c'(c_i,h_i)}{u_h'(c_i,h_i)}$ is the marginal rate of substitution between consumption and hours for workers in firms of productivity level i. $\varepsilon_{Y,X} = \frac{dY}{dX}\frac{X}{Y}$ denote the elasticity of Y w.r.t. X. Therefore,

the overall optimality condition is,

$$1 - \left[\frac{\varepsilon_{\pi_H,\tau}\pi_H + \varepsilon_{\pi_L,\tau}\pi_L}{E} + \varepsilon_{h_L,\tau}\frac{h_L}{1-h_L} + \varepsilon_{n,\tau}\frac{b - \tau(1-\rho)w(1-h_L)}{\tau w(1-h_L)}\right] =$$

$$\varepsilon_{h_H,\tau}\frac{n_H \cdot h_H\left[w - MRS_{c,h}^H\right]}{E}\mathbb{G}_H\frac{1-\rho}{\rho} + \varepsilon_{h_L,\tau}\frac{h_L\left[w(1-\tau) - MRS_{c,h}^L\right]}{E}g_L$$

$$+ \varepsilon_{\theta,\tau}\frac{\theta\Phi'(\theta)\Delta}{E} + \mathbb{G}_L\,.$$

We assume, based on empirical evidence, that $\varepsilon_{h_H,\tau} \approx 0$. Using this and rewriting the effect on profits into the externalities component yields,

$$1 + \left\{\varepsilon_{n,\tau}\frac{(1-\rho)b^{STW} - b}{b^{STW}} - \varepsilon_{h_L,\tau}\frac{h_L}{\bar{h} - h_L}\right\} = \varepsilon_{h_L,\tau}\frac{n_L \cdot h_L}{E}\left\{[w(1-\tau) - MRS_{c,h}^L]\,\mathbb{G}_L + (F_L^h - n_L)\right\}$$

$$+ \varepsilon_{\theta,\tau}\frac{\theta}{E}\left\{\Phi'(\theta)\Delta + q'(\theta)\mathcal{C}\right\} + \mathbb{G}_L,$$

where $b^{STW} = \tau w(\bar{h} - h)$ is the total amount of STW benefits for a worker in the program. $F_L^h = \frac{\epsilon_L}{n_L} \cdot \frac{\partial F(h_L, n_L)}{\partial h}$ is the marginal product of an increase in hours in low productivity firms and $\mathcal{C} = c \cdot v$ is total recruiting costs.

E.2   Local Calibration of Optimal STW Using Reduced-Form Estimates

Value of Transfer   To calibrate the social value of transfer $\mathbb{G}_L = \frac{\Omega_L}{n_L}\frac{u_c'(c_L, h_L)}{\mu}$, we first focus on the term $\frac{u_c'(c_L, h_L)}{\mu}$. This term refers to the marginal utility of consumption of treated workers $(u_c'(c_L, h_L))$ relative to that of the whole population of workers $\mu = \mathbb{E}[u_c'(c, h)]$. To calibrate this, we use our event studies estimates of Figure 4 panel C. They show that treated workers have total earnings and transfers that are significantly below ($\approx 18\%$ lower) that of their matched non-treated workers from non eligible firms. This difference between treated workers and the matched non-treated workers from non eligible firms represent the difference in total earnings and transfer between treated workers and counterfactual average workers in the economy. To translate this difference in earnings and transfer into a difference in marginal utility of consumption, we further assume that workers do not have access to additional self insurance, and that utility is separable between hours and consumption. Using a simple first-order Taylor expansion, we have that $\frac{u_c'(c_L, h_L)}{\mu} = \frac{u_c'(c_L, h_L)}{\mathbb{E}[u_c'(c, h)]} \approx 1 + \frac{u_c'(c_L, h_L) - u_c'(\bar{c}, h)}{u_c'(\bar{c}, h)} \approx 1 + \sigma_c\frac{\bar{c} - c_L}{\bar{c}}$. Using our estimates, this suggests that the wedge in marginal utility is approximately equal to $1 + \sigma_c \cdot .18$, where σ_c is the coefficient of relative risk aversion. The value of STW transfers is therefore potentially large. Assuming a coefficient of risk aversion of 2.5, (which is somewhat of the mid point of the accepted range of estimates in the literature), we get that $\frac{u_c'(c_L, h_L)}{\mu} \approx 1.45$

To calibrate $\frac{\Omega_L}{n_L}$ we use the definition of Ω_L and the observed values of time spent in the various states conditional on today's state and find $\frac{\Omega_L}{n_L} \approx 1$

As a result, our local calibration delivers $\mathbb{G}_L \approx 1.45$

Fiscal Externality We start with calibrating the first term of the fiscal externality, capturing the fiscal cost of employment responses: $\varepsilon_{n,\tau} \frac{(1-\rho)b^{STW}-b}{b^{STW}}$

This fiscal cost depends on the relative generosity of UI vs STW benefits: $\frac{(1-\rho)b^{STW}-b}{b^{STW}}$ To calibrate this, we set the unemployment benefit, b to match the net replacement rate for the average worker in Italy in 2008, which is around 70%. For our purposes, this is 70% of the wage obtained if working the full hours endowment $\bar{h} = 40$, i.e. $b = .7 \cdot w \cdot \bar{h}$. We set τ at its current level of 80%. ρ is the fraction of total employment from low productivity firms. To define low productivity firms, we use the fraction of eligible firms taking up STW during the Great Recession from 2009 to 2014= 13%. $h = 20$ is set to the average level of hours observed in these low productivity firms during the Recession. Using these values, we have that $\frac{(1-\rho)b^{STW}-b}{b^{STW}} = -1.62$.

We now calibrate the employment elasticity $\varepsilon_{n,\tau}$. We can decompose total employment response between low and high productivity employment responses $\frac{dn/n}{d\tau/\tau} = (1-\rho)\frac{dn_L/n_L}{d\tau/\tau} + \rho\frac{dn_H/n_H}{d\tau/\tau}$ To calibrate $\frac{dn_L/n_L}{d\tau/\tau}$ we use our estimate of the effect of STW on employment= $e^{.38}-1$=.45 To calibrate $\frac{dn_H/n_H}{d\tau/\tau}$ we use our spillover estimates: we know that employment decreases by .93% when the fraction treated increases by 1%. We also know that the availability of STW policy increases the fraction treated by 5% (our first stage estimate from Table 1). This means that $\frac{dn_H/n_H}{d\tau/\tau} = .0093*5$

Using again the fact that the fraction of low productivity firm is $1 - \rho$ =13% (which corresponds to the fraction of eligible firms ever taking up STW during recession), we have that the total employment response to the policy is $\varepsilon_{n,\tau} = .13*.45 - .87*(.0093*5) = 1.8\%$

The second term of the fiscal externality captures the hours response to the program: $-\varepsilon_{h_L,\tau}\frac{h_L}{\bar{h}-h_L}$. We can easily calibrate this term using the large estimated negative responses of hours to the policy from section 3.2: $\varepsilon_{h_L,\tau} = e^{-.51} - 1 = .4$. Using again $\bar{h} = 40$ and h=20, we find that the fiscal externality created by the hours response to the program is large and equal to .4., which trumps the small fiscal externality from employment responses.

The total fiscal externality, combining the employment and hours response is: $.018\cdot(-1.62)+.4 = .37$.

Employment externality To get a sense of the sign and magnitude of the employment externality, we proceed in two steps.

First, we calibrate the parameters of a Cobb-Douglas matching function from our reduced-form evidence to get a sense of the relative magnitude of $\Phi'(\theta)$ and $q'(\theta)$. All the details of this calibration exercize are reported below in Appendix E.2. Our estimate of the curvature of the matching function is .53. At low levels of tightness, such as during a recession, this curvature parameter implies that $\Phi'(\theta) > q'(\theta)$

Second, we turn to our event study estimates to get an idea of Δ, the lifetime utility gain from employment vs unemployment today. We use an approach similar to Shimer and Werning [2007] and look at the average drop in wage rate at reemployment vs prior to unemployment for unemployed

workers. This information tells us the willingness-to-pay to be employed vs unemployed, and provides an estimate of Δ. In our context, this drop is relatively large with an average wage rate drop around 8% at reemployment compared to pre-unemployment wage rate. How does Δ compare to $\mathcal{C}$, the total recruitment cost of an additional worker? We have very little evidence on $\mathcal{C}$. The most recent evidence from Mühlemann and Strupler [2015] using Swiss data, suggests recruiting costs vary between less than 2% of wages for large firms to around 20% for very small firms, and are sensitive to the business cycle. Overall, if we assume that $\mathcal{C}$ is actually close to Δ, the employment externality remains positive to the extent that $\Phi'(\theta) > q'(\theta)$.

Hours Externality   Signing and calibrating the hours externality term remains tricky in practice.

We proceed in two steps. First, we examine the term $[F_L^h - w]$. By implicitly differentiating the FOC of firms profit maximization w.r.t employment, we get that the employment response of low productivity firms to their change in hours with STW is an increasing function of the wedge between wages and the marginal product of hours: $\frac{dn_L}{dh_L} = f(w - F_L^h)$. In other words, the large observed employment responses to STW indicate that $[F_L^h - w] < 0$ and that the wedge is potentially large in magnitude.

Second, we examine the second term $w(1 - \tau) - MRS_{c,h}^L$. When workers freely choose hours in a complete market for hours, their optimal choice of hours is such that the MRS is equal to the net-of-tax wage rate. Interestingly, there is ample evidence that the fraction of workers reporting that they are willing to work more hours increases drastically during recessions (e.g. Canon, Kudlyak and Reed [2014]). This would indicate that recessions are actually characterized by $w(1 - \tau) - MRS_{c,h}^L \geq 0$. In which case decreasing equilibrium hours has a negative externality on workers.

Appendix F: Model Calibration & Counterfactual Analysis

The following appendix describes the details of the calibration of the model: the choice of functional form specifications, the calibration of the various parameters using quasi-experimental evidence, the GMM estimation of the parameters that could not be directly calibrated from reduced-form evidence, and the details of the counterfactual exercizes.

F.1 Exogenous parameters

Parameter	Description	Calibrated value
β	Discount factor	0.935
α	Hour share	0.6
η	Labour share	0.7
γ	Matching function curvature	0.53
w_a	Wage function curvature	0.2
$\bar{h}$	Total hours endowment	40
δ	Separation rate	0.05
b	Unemployment benefit	$0.7 \cdot \bar{h} \cdot w_s$
τ	STW replacement rate	0.8
σ_c	Coefficient of risk aversion	2.5
σ_h	Inverse of Frisch elasticity of labour supply	3.5
π	Markov transition matrix of firm productivity	[0.88 0.12; 0.88 0.12]
ϵ	Productivity values	[1 1.62]

F.1.1 Matching function, γ

We consider the Cobb-Douglas matching function:

$$M(u_t, v_t) = \mu u_t^\gamma v_t^{1-\gamma} \tag{22}$$

The vacancy filling probability $q(\theta)$ is therefore, as above:

$$q(\theta_t) = \frac{M(u_t, v_t)}{v_t} = \mu \left(\frac{u_t}{v_t}\right)^\gamma = \mu \theta_t^{-\gamma} \tag{23}$$

Log linearizing the above equation yields:

$$\ln(\frac{M}{v_t}) = \ln(\mu) - \gamma ln(\theta) \tag{24}$$

To obtain information on the measures of hires per vacancy, M/v_t, labor market tightness at the local labor market level, θ we use the RIL 2007, 2010 and 2015 surveys from ISTAT. Using

question C7 (and question C8 for 2015) we can compute $v_{j,t}^{RIL}$ the total number of vacancies (number of individuals the firm seeks to hire) in the RIL data at time t in labor market j.

To scale the vacancies in the RIL data to the whole local labor market level, we use the ratio of total employment of firms in the RIL data at time t in labor market j to total employment at time t in labor market j computed from the INPS administrative data, that is we have:

$$v_{j,t} = \frac{n_{j,t}}{n_{j,t}^{RIL}} \cdot v_{j,t}^{RIL} \tag{25}$$

Once a measure of vacancies $v_{j,t}$ is obtained, this is combined with measures of matches $M_{j,t}$ and of unemployment $u_{j,t}$ from the INPS data to create $q_{j,t}$ and $\theta_{j,t}$. For $M_{j,t}$ we compute the total number of new hires (inflows) in firms of LLM j in year t from the INPS data, and for $u_{j,t}$ we compute the total number of unemployed in LLM j at time t from the INPS data on paid unemployment.

We therefore can run the following specification:

$$\log q_{j,t} = a + b \log(\theta_{j,t}) + c_j + \zeta_t + \nu_{j,t} \tag{26}$$

For b to identify $-\gamma$, exogenous variation in $\theta_{j,t}$ is required. We use exposure to CIG treatment as an instrument. Intuitively, the intensity of CIG treatment offers an exogenous shock to labor demand in the LLM as depicted in Figure D-1 panel C. This shock allows us to move along the "supply curve" of steady state equality of flows in the labor market, and therefore identify the curvature of the matching function. We use again the interaction between firm size and INPS codes in the pre-recession period as an instrument for the change in the number of unemployed (and therefore for the change in tightness) during the recession. Therefore, we obtain the 2SLS model:

$$\Delta \log q_{j,t} = b \Delta \log\left(\hat{\theta}_{j,t}\right) + \zeta_t + \nu_{j,t} \tag{27}$$

$$\Delta \log(\theta_{j,t}) = CIG_j^{2005-2008} + \mu_{j,t}$$

where Δ is the difference operator pre vs post 2008. From this specficaition, we obtain $\gamma = 0.53$.

F.1.2 Production function, α and η

We assume that the production function of the firm is of the form:

$$F(h_t, n_t) = h_t^\alpha n_t^\eta \tag{28}$$

Log-linearization of the first order condition of the firm's profit maximization with respect to employment gives:

$$\log n = \frac{\alpha}{1-\eta} \log h - \frac{1}{1-\eta} \log(wh) - \frac{1-\beta(1-\delta)}{1-\eta} \frac{c}{whq(\theta)} + \frac{1}{1-\eta} \log(\varepsilon\eta) \tag{29}$$

Letting $\nu = \frac{1}{1-\eta} \log(\varepsilon \eta)$, and re-arranging we obtain:

$$\log n = \frac{\alpha - 1}{1 - \eta} \log h - \frac{1}{1 - \eta} \log w - \frac{1 - \beta(1 - \delta)}{1 - \eta} \frac{c}{whq(\theta)} + \nu \tag{30}$$

A third specification can be obtained through consolidating the whole wage bill as follows: $W = w\bar{h} + (h^{max} - \bar{h})\tau_f w$. Before 2015, the experience rating of the STW program was almost zero: $\tau_f \approx 0$ so $W = wh$ but after 2015, the introduction of $\tau_f > 0$ for firms on CIG introduces some exogenous variation in the wage bill. The new specification becomes:

$$\log n = \frac{\alpha}{1 - \eta} \log h - \frac{1}{1 - \eta} \log W - \frac{1 - \beta(1 - \delta)}{1 - \eta} \frac{c}{W \cdot q(\theta)} + \nu \tag{31}$$

The previous log-linearisation suggests the following estimation model:

$$\log n_{i,j,t} = \gamma_i + \zeta_j + \mu_t + \alpha_1 \log h_{i,j,t} + \alpha_2 \log W_{i,j,t} + \alpha_3 \underbrace{\frac{1}{W_{i,j,t}q(\theta_{j,t})}}_{X_{i,j,t}} + \nu_{i,j,t}$$

where i indexes firms, and j indexes LLM. Structurally, the coefficients from this regression α_1 and α_2 and α_3 identify the key parameters of the demand function. We estimate the previous specification instrumenting the change in hours by STW treatment and the change in the wage bill by the interaction of STW treatment and being after 2015, when the reform introduced some positive experience rating $\tau_f > 0$. Solving for these parameters gives $\alpha = 0.6, \eta = 0.7$.

F.1.3 Utility function

We use the following isoelastic, additively separable utility function:

$$u(c, h) = \frac{c^{1-\sigma_c} - 1}{1 - \sigma_c} - \varphi \frac{h^{1+\sigma_h}}{1 + \sigma_h} \tag{32}$$

σ_c, the coefficient of risk aversion is set to 2.5. The parameter σ_h can be interpreted as the inverse of the Frisch labour supply elasticity. We set this parameter to $\sigma_h = 3.5$ in line with conventional calibrations from New Keynesian models (see Galí [2011]).

F.1.4 Firm productivity transition matrix

Assume a firm's productivity level can take the value of one of two states, high and low (H and L). Assume that firms transition between these two states freely, where the probability of transitioning from one state to the other is solely dependent on the state which a firm finds themselves in. We therefore obtain the following Markov transition matrix, where π_{ST} is the conditional probability of moving to state S, conditional on being in state T:

From this transition matrix, we obtain the following equations, telling us the total number of

$$
\begin{array}{c|cc}
 & \epsilon_t = \text{H} & \epsilon_t = \text{L} \\
\hline
\epsilon_{t+1} = \text{H} & \pi_{HH} & 1 - \pi_{HH} \\
\epsilon_{t+1} = \text{L} & 1 - \pi_{LL} & \pi_{LL}
\end{array}
$$

Table F-1: Markov transition matrix between productivity states

firms in each state in the next period. Let n_t^i be the number of firms in state i at time t:

$$\pi_{HH} \cdot n_t^h + (1 - \pi_{LL}) \cdot n_t^l = n_{t+1}^h \tag{33}$$

$$\pi_{LL} \cdot n_t^l + (1 - \pi_{HH}) \cdot n_t^h = n_{t+1}^l$$

Assume that we observe the steady state:

$$n_t^h = n_{t+1}^h = n_h \tag{34}$$

$$n_t^l = n_{t+1}^l = n_l$$

And we therefore obtain:

$$\pi_{HH} \cdot n^h + (1 - \pi_{LL}) \cdot n^l = n^h \tag{35}$$

$$\pi_{LL} \cdot n^l + (1 - \pi_{HH}) \cdot n^h = n^l$$

It's clear that these two equations in fact provide no new information, and both reduce to:

$$(1 - \pi_{HH}) \cdot n^h = (1 - \pi_{LL}) \cdot n^l \tag{36}$$

However, we also have an extra condition as were in the steady state the proportions π_{HH} and π_{LL} must add up to 1. We therefore obtain two equations:

$$\pi_{HH} + \pi_{LL} = 1 \tag{37}$$

$$(1 - \pi_{HH}) \cdot n^h = (1 - \pi_{LL}) \cdot n^l$$

Which reduces to simply:

$$\pi_{HH} = n^h / (n^l + n^h) \tag{38}$$

We must define now define how to interpret productivity within the data. Take low productivity firms as those who are eligible for CIG and who have at least one CIG event in post 2009. High productivity firms are those eligible but do not take up CIG at any point post 2009.

We observe that 13% of firms are treated post 2009 in the baseline DD sample. We thus obtain $\pi_{HH} = 0.87$. Further, taking the mean (log) total factor productivity of these firms, and normalising the low productivity value to 1 yields: $\epsilon_l = 1, \epsilon_h = 1.62$.

F.1.5 Wage schedule and hours schedule

We assume that the wage has the following form:

$$w(\epsilon) = w_s \epsilon^{w_a} \tag{39}$$

with $w_a < 1$. The wage is therefore a somewhat rigid function of productivity. Besides, it does not respond to variation in the STW subsidy, nor to variation in hours, consistent with our empirical evidence. The wage responsiveness to firm productivity, w_a, is set to 0.2, in line with similar models in the literature, c.f. Landais, Michaillat, Saez (2018).

The hours schedule in the low productivity firm is obtained by assuming that firms have all the bargaining power in low productivity firms, therefore leaving workers at their outside option. For high productivity firms, we consider a simple exogenous hours schedule:

$$h(\theta, \epsilon) = hs_s \epsilon^{hs_a} \theta^{hs_b} \tag{40}$$

To estimate the parameter hs_b, the responsiveness of the hours function to a change in labour market tightness, we regress log hours among ineligible firms at LLM level against log tightness, instrumented by eligibility of CIG. This model obtains a coefficient of 0.14.

F.1.6 Transfer generosity

The unemployment benefit, b, is set to match the net replacement rate for the average worker in Italy in 2008, which is around 70%. For our purposes, this is 70% of the wage obtained if working the full hours endowment.

The STW replacement rate, τ, is the policy parameter, which is determined by the legal implementation of CIG. This rate is defined as 80% of the total remuneration that would have been paid to the worker for the hours of work not provided, bounded between 0 and the fully contracted time.

F.1.7 Miscellaneous parameters

The model imposes an exogenous separation rate, δ. This is set to 0.2, which is the implied probability of being displaced from an specific firm in a specific contract. The model's discount factor, β, is set to 0.935, implying an annual interest rate of 7%.

F.2 Endogenous parameters & target moments

After setting the exogenous parameters, we are left with 5 endogenous parameters:

Parameter	Description
μ	Matching function scaling
c	Vacancy cost
φ	Utility function labour scaling
hs_a	Hours schedule productivity curvature
w_s	Wage function scaling

We obtain these parameters through the method of simulated moments, with five target moments:

Target Moments	Value
Unemployment rate	0.108
High productivity hours level	34
Low productivity hours level, without STW	39
Low productivity hours level, with STW	20
Proportion of labour demand that is high productivty	0.9

The target unemployment rate is the Italian unemployment rate as obtained in the INPS/RIL data, post 2008: 0.108. Low productivity firms is defined as:

- For eligible firms, those that take up CIG.

- For non-eligible firms, in eligible 5-digit industries, firms whose total factor production is in the bottom 12% of the distribution, post 2009.

F.3   Counterfactual Analysis: Permanent vs Transitory Shocks

Our baseline calibration considers the Great Recession in Italy as a steady state, and asks what the value is, in such a steady state, of having STW subsidies target firms with negative idiosyncratic shocks. But the nature of shocks, whether they are permanent or transitory, aggregate or idiosyncratic, may matter as well in assessing the effects of STW policies. Firms may be more willing to hoard labor when they expect a shock to be temporary, and therefore relaxing constraints to labor hoarding may be more effective for temporary shocks. Our previous analysis in Figure 5 indeed indicates that employment effects of STW are larger for firms that were high productivity prior to the recession, suggesting that STW may be more effective for high productivity firms experiencing a transitory negative shock than for permanently low productivity firms. To get further insights on this, we now use our calibrated model and simulate the effects of STW under two different scenarii of aggregate shocks: a permanent shock and a transitory shock. In both scenarii, we start from the steady state, and firms face in period 0 a surprise 10% negative aggregate productivity shock. In the first case, the shock is permanent, in the second, the shock is only transitory and the aggregate productivity level recovers linearly over 3 periods. Note that in both cases, the initial
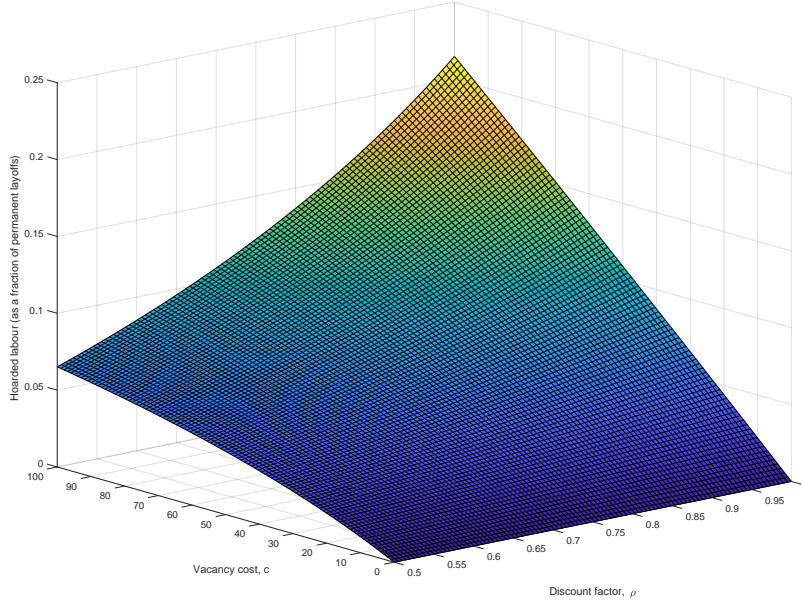
shock in period 0 is unexpected, but firms then have rational expectations with respect to future states of aggregate productivity (i.e. they know, once realized, whether the shock is permanent or transitory).

The simulated employment response on impact (at time 0) to the permanent shock ($\dot{n}(0)|_{\text{perm.}}$) is, not surprisingly, larger than the employment response to the temporary shock ($\dot{n}(0)|_{\text{temp.}}$).Figure F-1 panel A shows the difference in simulated employment responses $\dot{n}(0)|_{\text{temp.}} - \dot{n}(0)|_{\text{perm.}}$, expressed as a fraction of the employment loss to the permanent shock $-\dot{n}(0)|_{\text{perm.}}$, for various values of the discount factor and of the hiring costs $\mathcal{C}$. The graph confirms that, in the transitory shock scenario, firms do "hoard labor" on impact and keep 10 to 15% of the workers that they would get rid of if they knew the shock was permanent. Importantly, the figure shows that labor hoarding is significantly larger when the cost to firms of replacing their workers increases.

Because hoarding is more valuable when the shock is transitory then permanent, the employment effects of having STW also differ according to the permanence of the aggregate shock. To document this, we simulate $\dot{n}(0)|_{\text{perm.}}$ and $\dot{n}(0)|_{\text{temp.}}$ in a world without STW ($\tau = 0$), and compute the employment effects of STW, $\Delta\dot{n}(0) = \dot{n}(0)|^{\tau=.8} - \dot{n}(0)|^{\tau=0}$, in both scenarii of the aggregate shock. Panel B of Figure F-1 plots the difference in employment effects of STW, $\Delta\dot{n}(0)|_{\text{temp.}} - \Delta\dot{n}(0)|_{\text{perm.}}$, expressed relative to the employment effects of STW in the permanent shock scenario $\Delta\dot{n}(0)|_{\text{perm.}}$. The graph confirms that the employment effects of STW on impact are significantly larger (around 20% to 40%) when the shock is temporary than when it is permanent. This, again, is especially true when the cost of replacing workers is high, and when the magnitude of the aggregate shock is large.

Figure F-1: LABOR HOARDING AND MAGNITUDE OF STW EFFECTS ON EMPLOYMENT: TRANSITORY VS PERMANENT AGGREGATE SHOCK

A. Simulated Labor Hoarding for Transitory Shock

B. Employment Effects of STW
for Transitory vs Permanent Shock
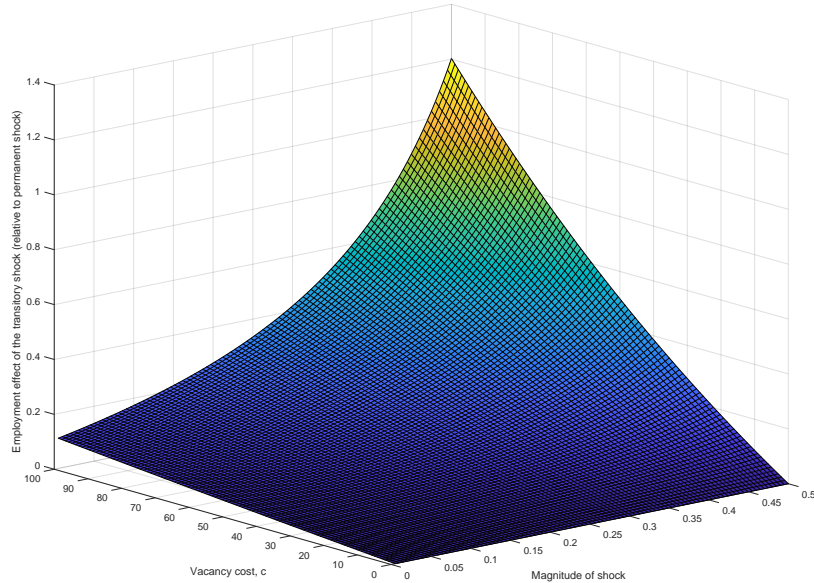
Notes: The Figure uses the calibrated model to simulate the extent of labor hoarding and the employment effects of STW under two different scenarii of aggregate shocks: a permanent shock and a transitory shock. In both scenarii, we start from the steady state, and firms face in period 0 a surprise 10% negative aggregate productivity shock. In the first case, the shock is permanent, in the second, the shock is only transitory and the aggregate productivity level recovers linearly over 3 periods. Once the shock is realized, firms have rational expectations with respect to future states of aggregate productivity. Panel A shows the difference between the simulated employment response on impact (at time 0) to the permanent shock $(\dot{n}(0)|_{\text{perm.}})$ to the employment response to the temporary shock $(\dot{n}(0)|_{\text{temp.}})$. expressed as a fraction of the employment loss to the permanent shock $-\dot{n}(0)|_{\text{perm.}}$, for various values of the discount factor and of the costs of replacing workers $\mathcal{C}$. The graph confirms that, in the transitory shock scenario, firms do "hoard labor" on impact and keep 10 to 15% of the workers that they would get rid of if they knew the shock was permanent. We then simulate $\dot{n}(0)|_{\text{perm.}}$ and $\dot{n}(0)|_{\text{temp.}}$ in a world without STW $(\tau = 0)$, and compute the employment effects of STW, $\Delta\dot{n}(0) = \dot{n}(0)|^{\tau=.8} - \dot{n}(0)|^{\tau=0}$, in both scenarii of the aggregate shock. Panel B plots the difference in employment effects of STW, $\Delta\dot{n}(0)|_{\text{temp.}} - \Delta\dot{n}(0)|_{\text{perm.}}$, expressed relative to the employment effects of STW in the permanent shock scenario $\Delta\dot{n}(0)|_{\text{perm.}}$. The graph confirms that the employment effects of STW on impact are significantly larger (around 20% to 40%) when the shock is temporary than when it is permanent.