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

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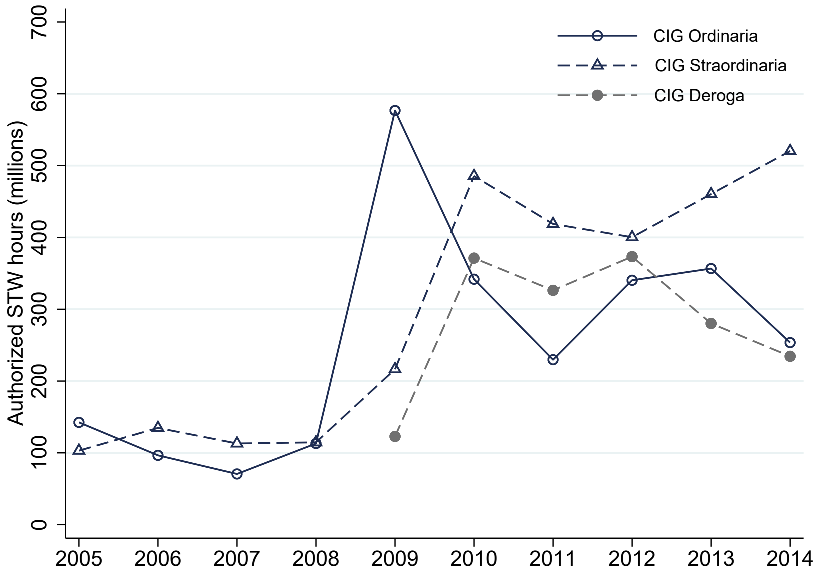
A Additional Figures & Tables

A.1 Descriptive Statistics

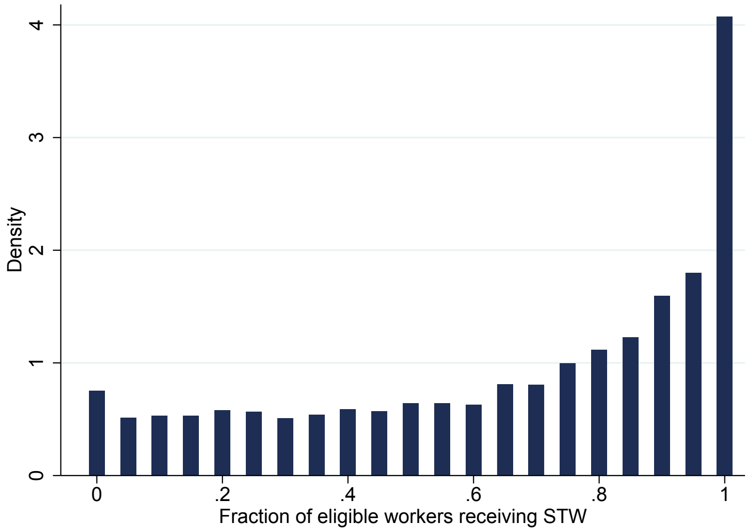
Figure A-1: TIME SERIES OF AUTHORIZED SHORT TIME WORK HOURS BY PROGRAM TYPE



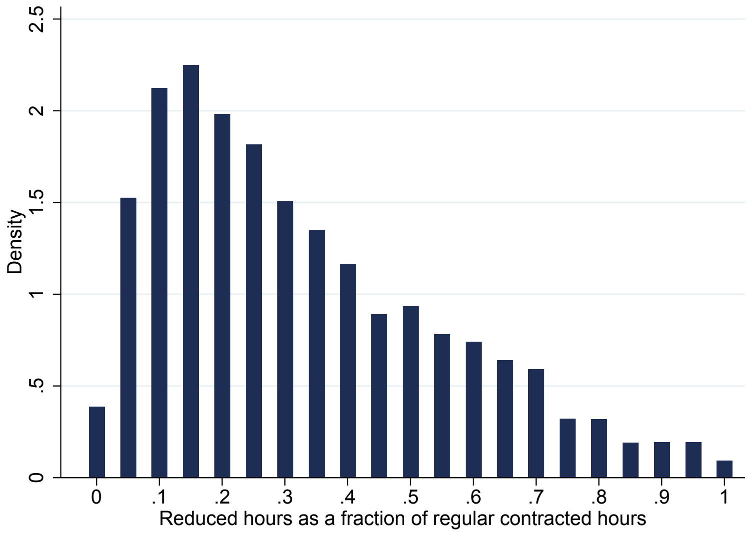
Notes: The graph reports the time series of authorized hours (in millions) by program type from 2005 to 2014.

Figure A-2: DISTRIBUTION OF SHORT TIME WORK TREATMENT ACROSS WORKERS IN FIRMS EXPERIENCING SHORT TIME WORK

A. Distribution of Fraction of Eligible Workers on STW in Treated Firms



B. Distribution of Reported Weekly Hour Reductions across Treated Workers



Notes: The figure reports descriptive statistics on the distribution of treatment across workers in firms experiencing STW. Panel A plots the distribution of the ratio of treated workers to eligible workers in firms currently using STW. Panel B reports the distribution of reported weekly hour reductions for workers on STW, that is hours on STW out of regular contractual weekly hours. The latter are assumed to be 40 for full-time workers, and 40 times the share of part-time for part-time workers (as reported in the INPS data). The mode is around .25 and the average around .35.

Table A-1: Distribution of Authorized Hours and Applications, by Short Time Work Scheme and Reason for Application

Reason for application	Share of Authorized Hours 2005-2008 (1)	2009 (2)	2010-2014 (3)	Share of Authorized Applications 2005-2008 (4)	2009 (5)	2010-2014 (6)
CIGO						
Adverse weather conditions	.35	.07	.13	.93	.71	.72
Market crisis	.03	.02	.16	.00	.01	.05
Slump in demand	.59	.89	.68	.06	.27	.21
Other	.03	.01	.03	.01	.01	.02
CIGS						
Company crisis	.38	.65	.46	.46	.69	.57
Restructuring/Reorganization	.25	.09	.18	.14	.06	.08
Bankruptcy	.16	.09	.16	.21	.13	.15
Special administration	.09	.04	.02	.05	.03	.01
Business closure	.00	.00	.03	.00	.00	.02
Other	.12	.13	.15	.14	.09	.17
CIGD						
Total	-	1.0	1.0	-	1.0	1.0

Notes: The table reports the distribution of authorized hours (columns 1-3) and authorized applications (columns 4-6) across categories of reasons for application, by program type (CIGO, CIGS and CIGD) and time period, distinguishing between the pre-crisis years 2005-2008, the year 2009 and the crisis years 2010-2014. The INPS data do not report the specific reason for application for CIGD.

Table A-2: Distribution of Firms' Characteristics in the Main Sample by 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 tangibles	0.07	0.11	0.07	0.10	0.07	0.11
Investment in intangibles	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.

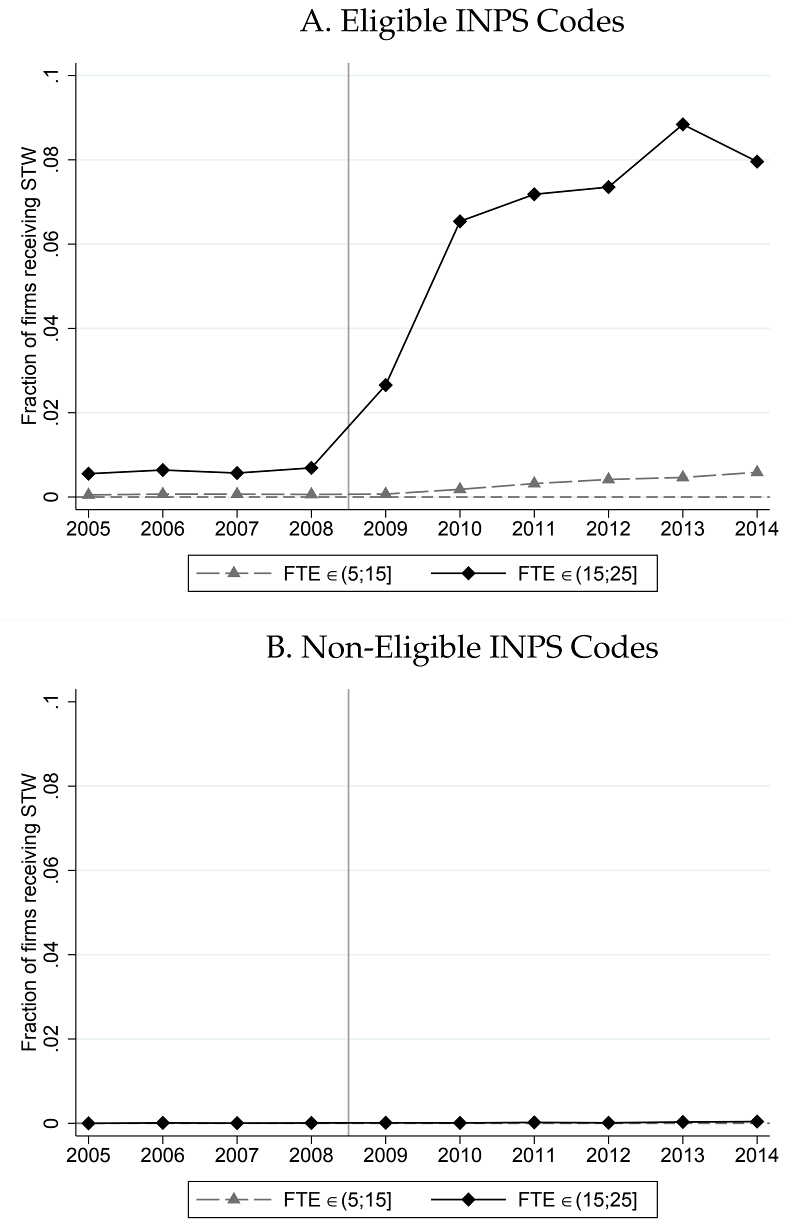
Table A-3: DISTRIBUTION OF WORKERS' CHARACTERISTICS IN THE MAIN SAMPLE BY ELIGIBLE AND NON-ELIGIBLE INPS CODES (2008)

	(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
Prop. on full-time contract	0.82	0.38	0.90	0.30	0.78	0.42
Prop. on open-ended contract	0.83	0.37	0.88	0.32	0.81	0.40
Prop. on fixed-term contract	0.15	0.36	0.12	0.32	0.17	0.38
Prop. 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

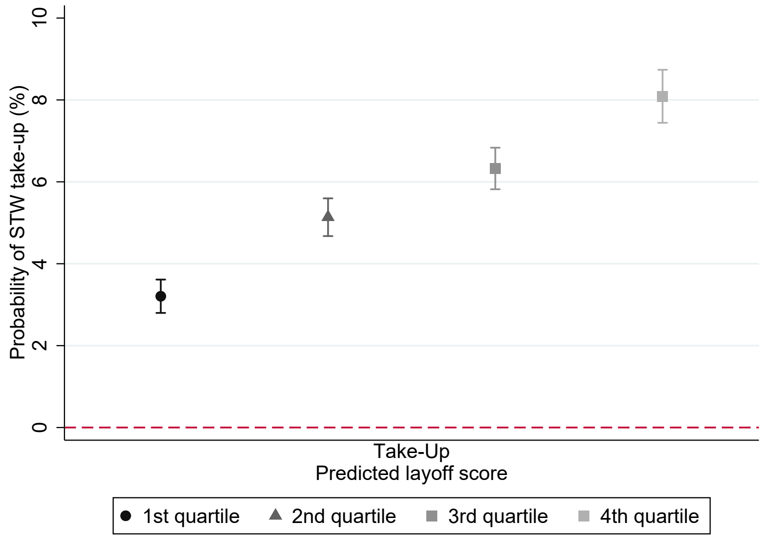
Figure A-3: FRACTION OF FIRMS RECEIVING SHORT TIME WORK BY FIRM SIZE & INPS CODE



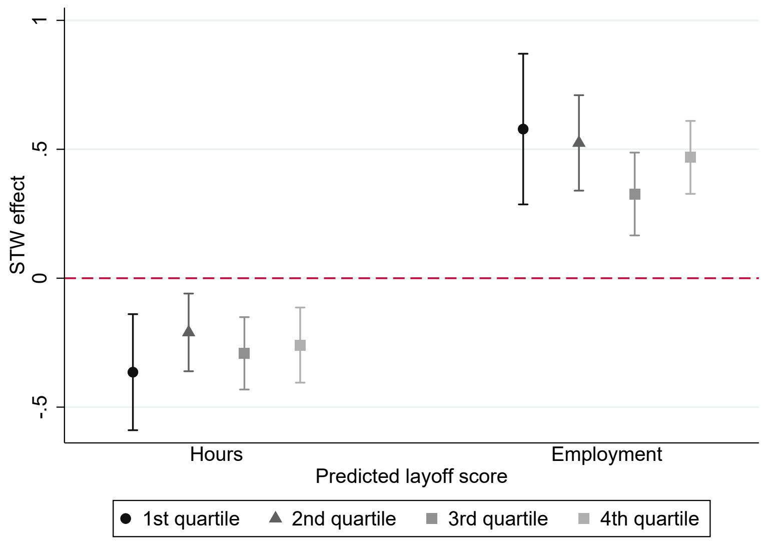
Notes: The graphs show the fraction of firms receiving STW in each calendar year $t \in [2005, 2014]$ by eligibility status and maximum 6-month average FTE firm size in year $t-1$. Panel A plots, among firms with eligible INPS codes in our sample, the evolution of the fraction of firms receiving STW in each calendar year t from 2005 to 2014, for firms with a maximum 6-month average FTE size $\in (15, 25]$ in year $t-1$ and for firms with a maximum 6-month average FTE size $\in (5, 15]$ in year $t-1$. Panel B replicates Panel A for firms in non-eligible INPS codes.

Figure A-4: EFFECTS OF SHORT TIME WORK BY PREDICTED LAYOFF-RISK SCORE

A. Take-Up

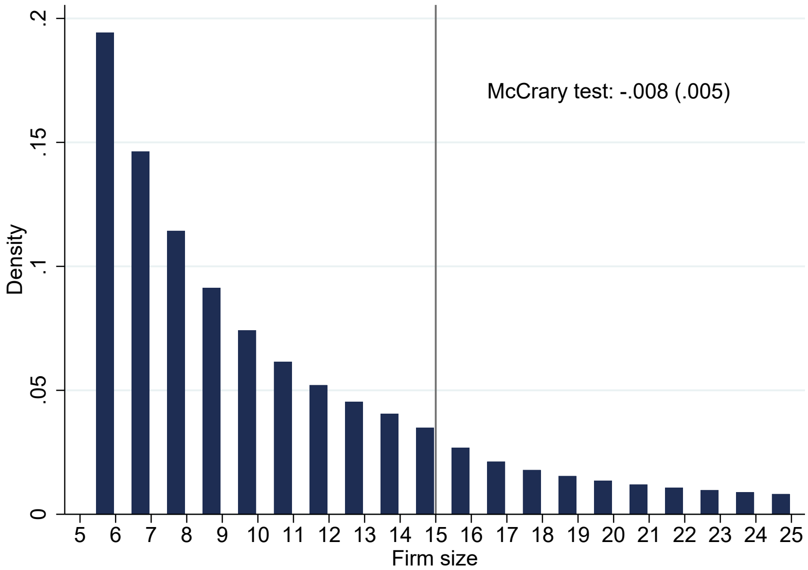


B. Hours and Employment



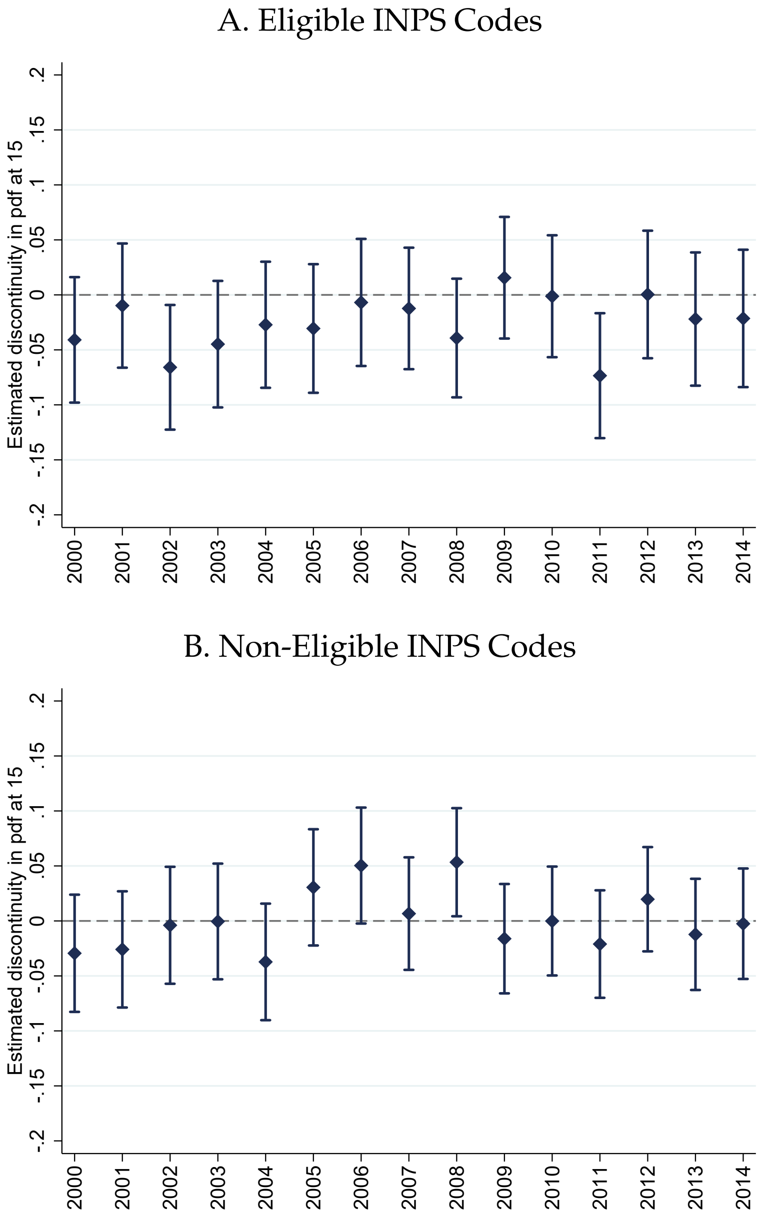
Notes: The graphs show heterogeneity in STW take-up and treatment effects by a score of the predicted probability that a firm experiences a mass layoff. The prediction model for the probability of mass layoff is described in Section 3.2. We rank firms into the four quartiles of the distribution of this score, and estimate specification (3) on the sample of firms in each quartile. Panel A displays the estimated coefficient $\widehat{\kappa}_1$ from specification (3) for the probability of STW take-up for firms at different quartiles of the distribution of the mass-layoff score. Panel B reports the IV estimates $\widehat{\beta}_{IV}$ from specification (2) for different outcomes, again splitting the sample in the four quartiles of the distribution and estimating the regression separately for each quartile. The vertical bars indicate 95% confidence intervals based on standard errors clustered at the INPS code times firm size group level.

Figure A-5: DISTRIBUTION OF FIRMS' FTE SIZE (2000-2014)



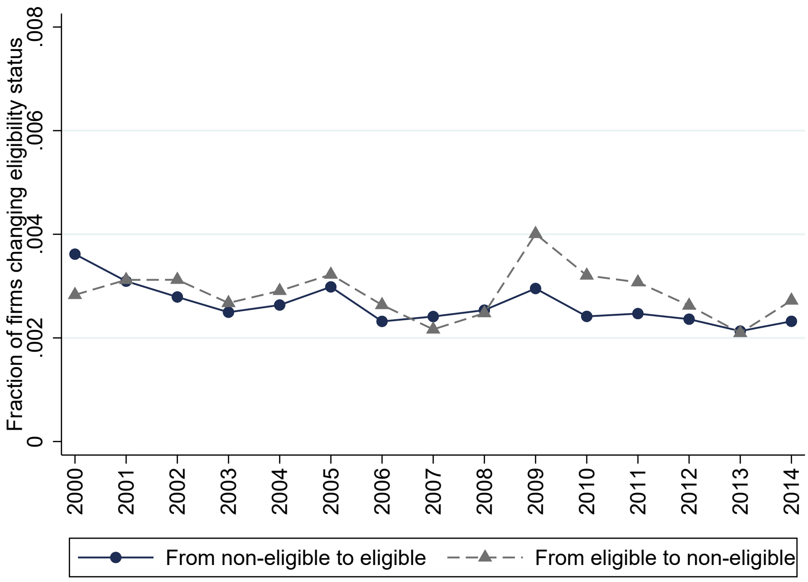
Notes: The graph shows the probability density function of FTE firm size by 1-unit bins for the years 2000-2014. The graph also reports the McCrary test statistic for the presence of a discontinuity in the probability density function of FTE size at 15 and its standard error. FTE firm size is defined 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 FTE units.

Figure A-6: McCrary Test Statistic of Discontinuity in Firm Size Distribution



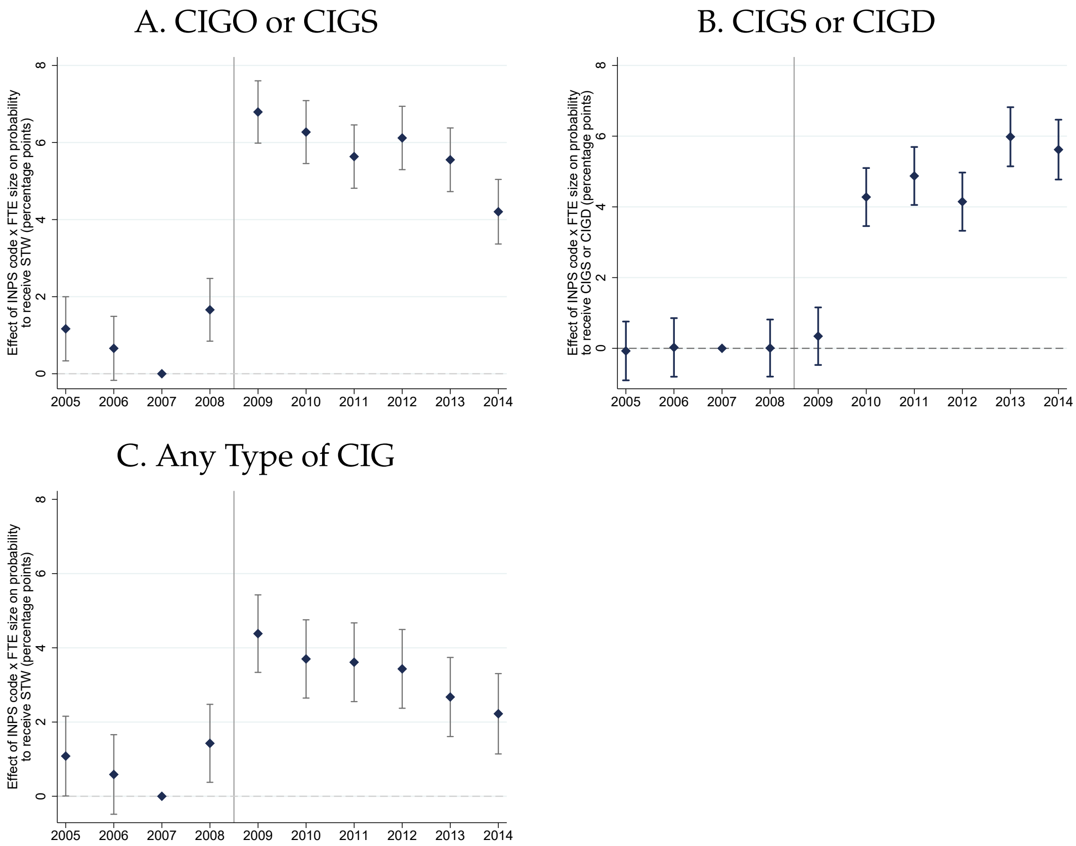
Notes: The graphs report the McCrary test statistic for the presence of a discontinuity in the probability density function of FTE size at 15 and its confidence interval for each year $t \in [2000, 2014]$, and for eligible and non-eligible INPS codes separately. The vertical bars indicate 95% confidence 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 FTE units.

Figure A-7: Fraction of Firms Changing Eligibility Status due to Changes in INPS Code (2000-2014)



Notes: The graph 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-8: Firms' Probability of Receiving CIGO, CIGS or CIGD by Firm Size & INPS Code



Notes: The graphs report the coefficients $\widehat{\gamma}_1^t$ estimated from equation (1) for all years $t \in [2005, 2014]$ using the probability of (i) CIGO or CIGS receipt in Panel A, (ii) CIGS or CIGD receipt in Panel B and (iii) any CIG (CIGO, CIGS or CIGD) receipt in Panel C at the firm level as outcome. The omitted year is 2007, so all results are relative to 2007. The vertical bars indicate 95% confidence intervals based on standard errors clustered at the INPS code times firm size group level.

Table A-4: EFFECTS OF TREATMENT ON FIRMS' AND WORKERS' OUTCOMES: SAMPLE OF FIRMS MATCHED TO BALANCE-SHEET DATA

	Estimate (1)	Std Error (2)	N (3)
	A. First Stage		
Probability of CIGS take-up	.042	(.002)	881276
	B. Employment Outcomes (IV)		
Log number of hours per employee	-.374	(.054)	881276
Log number of full-time weeks per employee	-.278	(.051)	881276
Log firm size (headcount)	.421	(.072)	881276
Log wage rate	.094	(.051)	881276
Log wage bill per employee	-.305	(.074)	881276
Log number of open-ended contracts	.597	(.087)	881276
Log number of fixed-term contracts	-.830	(.240)	881276
Rate of inflows	-.143	(.063)	881276
Rate of outflows	-.016	(.093)	881276
Firm survival probability (in $t+1$)	.032	(.020)	881276

Notes: Panel A reports the estimates of the coefficient $\widehat{\kappa}_1$ from specification (3) and its associated cluster-robust standard error in parenthesis. Panels B and C report the $\widehat{\beta}_{IV}$ coefficients estimated from equation (2) and their associated cluster-robust standard errors in parenthesis for a set of different firm-level outcomes. The wage rate is defined as total earnings per hours worked per employee. For survival probability, the reported coefficient is the IV estimate scaled by average survival probability in $t+1$: $\widehat{\beta}_{IV}/\bar{Y}$. The sample includes firms that have been linked to their balance-sheet data from CERVED.

Table A-5: EFFECTS OF OVERALL SHORT TIME WORK (CIG) TREATMENT ON FIRMS' OUTCOMES

	Estimate (1)	Std Error (2)	N (3)
Panel I. Baseline specification			
	A. First Stage		
Probability of any CIG take-up	.026	(.002)	2851216
Probability of CIGO take-up	.023	(.002)	2851216
Probability of CIGD take-up	-.023	(.002)	2851216
Probability of CIGO or CIGS take-up	.049	(.002)	2851216
	B. Employment Outcomes (IV)		
Log number of hours per employee	-.534	(.086)	2851216
Log number of full-time weeks per employee	-.553	(.083)	2851216
Log firm size (headcount)	.377	(.101)	2851216
Log wage rate	-.015	(.059)	2851216
Log wage bill per employee	-.693	(.107)	2851216
Log number of open-ended contracts	.441	(.106)	2851216
Log number of fixed-term contracts	-.557	(.276)	2851216
Firm survival probability (in $t+1$)	.069	(.023)	2851216
Panel II. Alternative specification			
	A. First Stage		
Probability of any CIG take-up	.078	(.006)	300795
	B. Employment Outcomes (IV)		
Hours per employee (inverse hyperbolic sine)	-.302	(.080)	300795
Firm size headcount (inverse hyperbolic sine)	.306	(.154)	300795
Firm survival probability	.291	(.045)	300795

Notes: Panel I.A reports the estimates of the coefficient $\widehat{\kappa}_1$ from our baseline first-stage specification (3) using various definitions of CIG treatment as outcome. Associated cluster-robust standard errors are reported in parenthesis. Panel I.B reports the $\widehat{\beta}_{IV}$ coefficients estimated from our baseline IV specification (2) using the take-up of any CIG program as treatment, for a set of different firm-level outcomes. Panels II.A and II.B report coefficient estimates (and associated cluster-robust standard errors) from our alternative specification illustrated in equations (6) and (5). Treatment is defined as take-up of any CIG program.

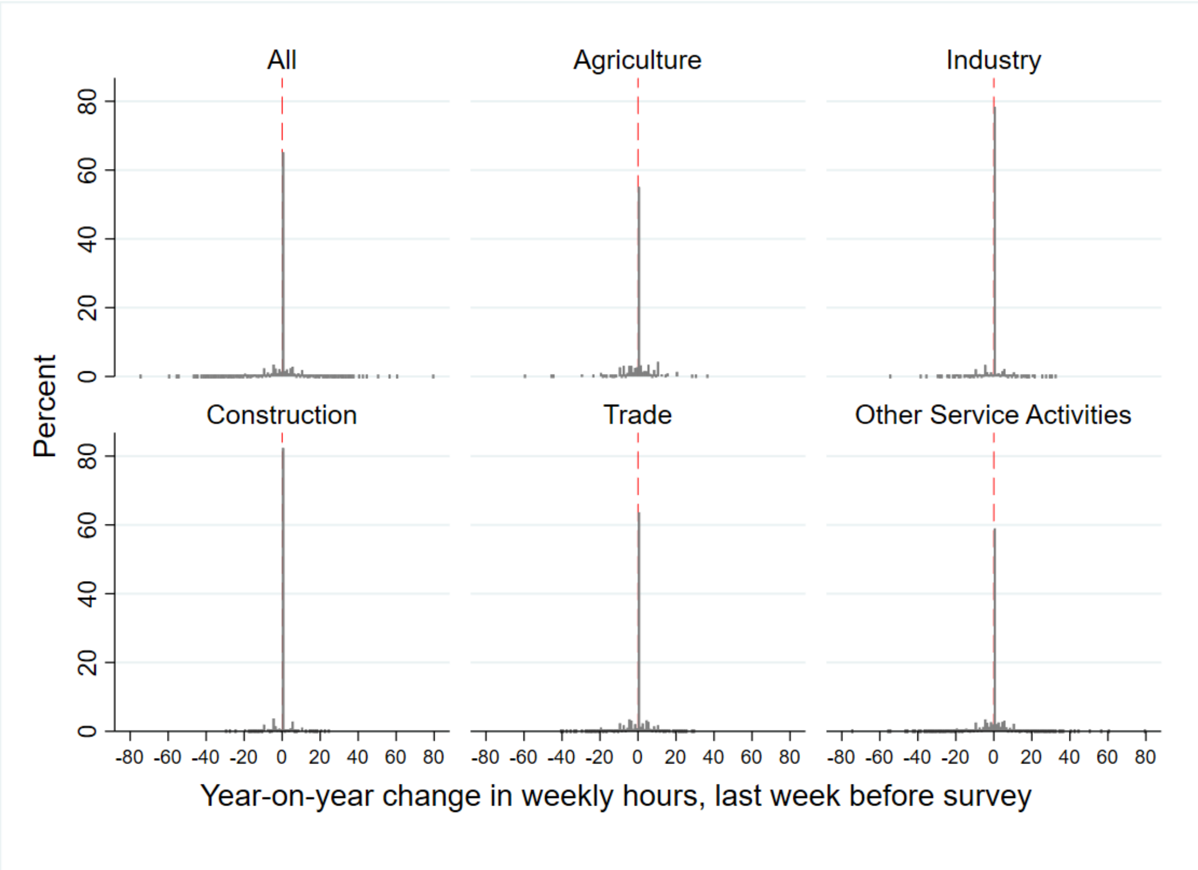
B Sources of Layoff Inefficiencies - Additional Details

B.1 Bargaining Efficiency

Figure B-1: HOUR AND WAGE RIGIDITIES

Notes: Panels A and B report the empirical distribution of the year-on-year change in log hourly wages and contractual weekly hours for the years 2010-2014. Year-on-year changes are binned into bins of 1-unit width. Contractual weekly hours can be directly observed in the INPS data starting from 2009 and correspond to the number of hours of work specified in the contract. Hourly wages are computed dividing contractual monthly earnings by contractual weekly hours (assuming 4.3 weeks per month). Both contractual monthly earnings and contractual weekly hours can be observed in the INPS data from 2009. Year-on-year changes are based on the values observed in March of each year. The sample is restricted to workers employed in occupations eligible for STW in non-eligible firms, and who are employed in the same firm over two consecutive years.

Figure B-2: HOUR RIGIDITIES BY SECTOR (LABOR FORCE SURVEY DATA)



Notes: The figure reports the empirical distribution of the year-on-year change in weekly hours worked for the years 2005-2014 by sector using data from the Italian Labor Force Survey. Year-on-year changes are binned into bins of 1-unit width. Weekly hours are self-reported actual hours worked in the week before the survey, conditional on having worked in that week. The sample is restricted to workers employed in occupations eligible for STW over two consecutive years and working at firms with less than 15 employees, i.e. that are not eligible for STW. In order to select workers who likely stayed in the same job over two consecutive years, we restrict the sample to workers who were in the same occupation and sector in t and $t-1$, and who were employed under a permanent contract in both periods.

B.2 Moral Hazard & Fiscal Externality

In this subsection, we derive the total fiscal externality created by behavioral responses to STW, and provide an estimate of the mark-up that society should be willing to pay on STW expenditures to make the current level of STW subsidy optimal.

There is a unit mass of identical workers in the economy. Workers can be either employed or unemployed. When employed, workers can either work full-time or be on STW. Employed workers pay a tax t on their labor income. The government budget constraint can be written as:

$$t \cdot w \cdot h \cdot n + t \cdot w \cdot \bar{h} \cdot (1 - n - u) = b \cdot w \cdot \bar{h} \cdot u + \tau \cdot w \cdot (\bar{h} - h) \cdot n$$

where u is the share of unemployed workers, and b is the replacement rate of the UI system. n is the share of employment on STW and h is the number of hours worked per worker in STW. The level of full-time hours is given by $\bar{h}$. Hours not worked below the full-time level $(\bar{h} - h)$ in firms using STW are subsidized at replacement rate τ. The hourly wage rate is w.

Differentiating the government budget constraint with respect to τ, assuming $du/d\tau = -dn/d\tau$, and rescaling by $n \cdot (\bar{h} - h)$, we obtain the fiscal externality for each unit of subsidy:

$$FE = 1 + \varepsilon_{n,\tau} \left(1 - \frac{b \cdot \bar{h}}{\tau \cdot (\bar{h} - h)} \right) - \varepsilon_{h,\tau} \cdot \frac{h}{(\bar{h} - h)}$$

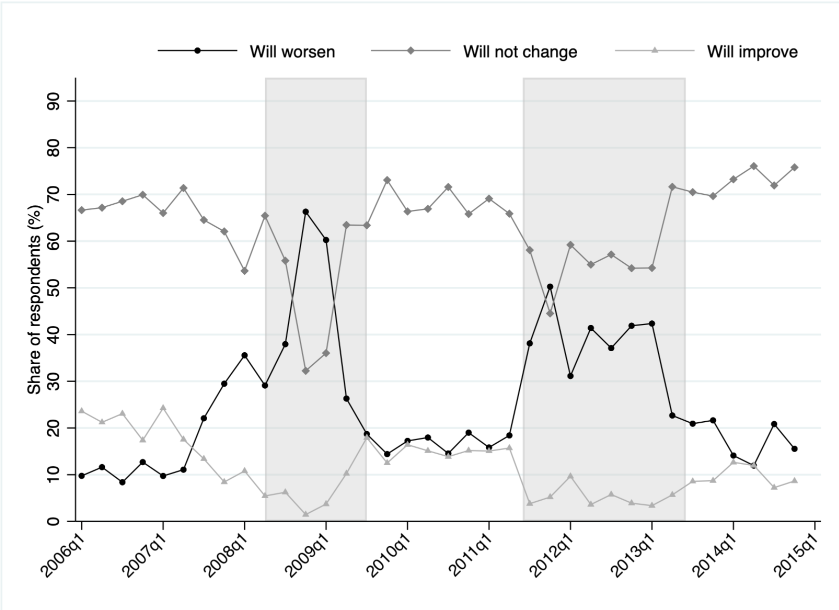
where $\varepsilon_{n,\tau}$ is the elasticity of employment to the STW subsidy, and $\varepsilon_{h,\tau}$ is the elasticity of hours to the STW subsidy. Calibrating the value of the fiscal externality using our estimates of the elasticity, a UI replacement rate of 70%, an STW replacement rate of 80% and a ratio of STW hours to full-time hours of 35% as per our results in Panel B of Figure A-2, we obtain a value of the fiscal externality of 1.38.

C Dynamic Treatment Effects

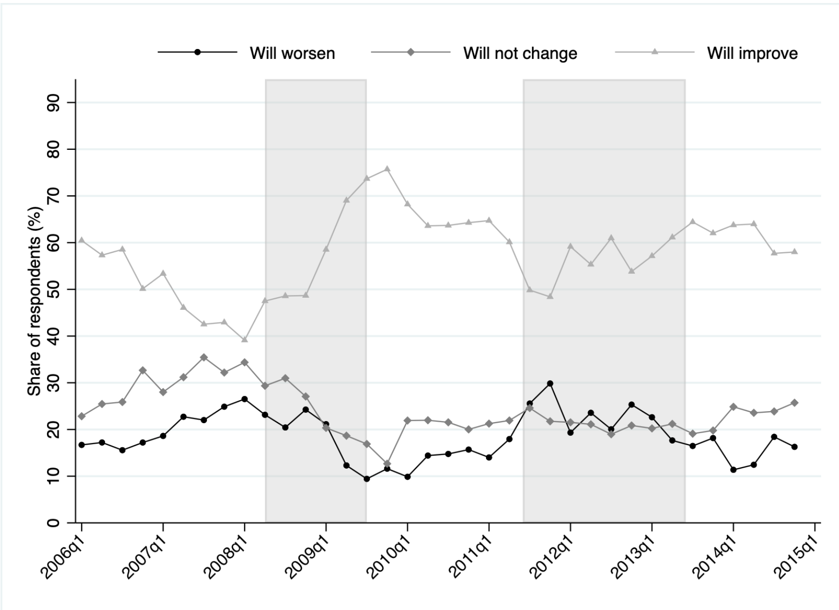
C.1 Persistence of the Recessionary Shock

Figure C-1: FIRMS' EXPECTATIONS ABOUT BUSINESS CONDITIONS

A. Over the Next Three Months

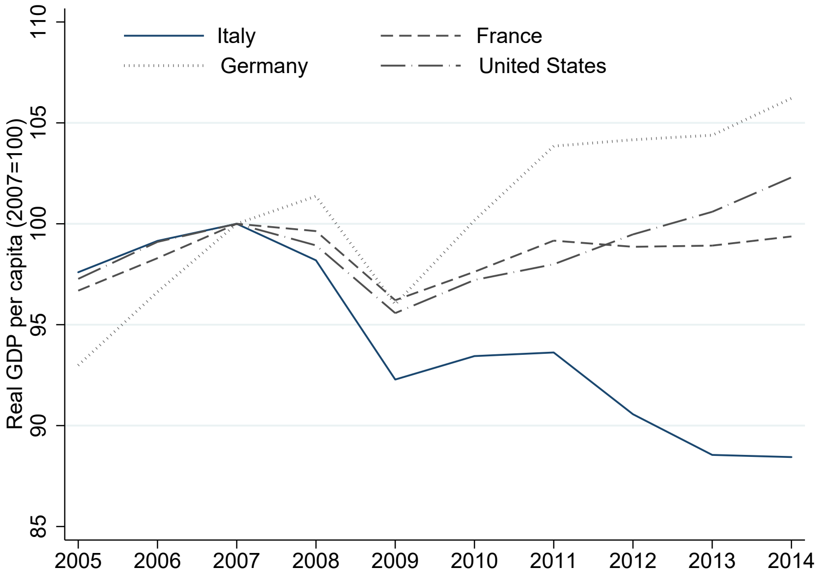


B. Over the Next Three Years



Notes: The graphs report evidence on answers to the question "How do you think business conditions for your company will be in the next 3 months?" (Panel A) and "in the next three years?" (Panel B). The shaded areas indicate recessionary periods, as identified by the FRED's OECD based Recession Indicators. Data come from the Bank of Italy Survey on Inflation and Growth Expectations.

Figure C-2: EVOLUTION OF REAL GDP PER CAPITA IN THE AFTERMATH OF THE FINANCIAL CRISIS IN EUROPE AND THE US



Notes: The graph reports the evolution of real GDP per capita in Italy, France, Germany and the United States. Each series is normalized to 100 in 2007. The data is taken from OECD.

C.2 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 Riegg, Ferreira and Rothstein [2010]. We would like to identify the sequence of dynamic Treatment-On-the-Treated effects $\{\beta_0^{TOT}, \beta_1^{TOT}, ..., \beta_k^{TOT}\}$, which capture the effect of STW treatment on a given 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 restrict our sample to 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_{2011}), etc. We also know from Appendix Figure C-3 that Z_{2009} is not correlated with treatment in the past (T_{2008}, T_{2007}, etc.). If, on this sample, we now run the following reduced-form of the baseline IV model (2) using Z_{2009} as an instrument:

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

the estimated reduced-form coefficients for each year 2009, 2010, etc. (β_{2009}^{RF}, β_{2010}^{RF}, etc.) capture the dynamic Intention-To-Treat (ITT) effects from 2009, letting potential future treatment occur. That is:

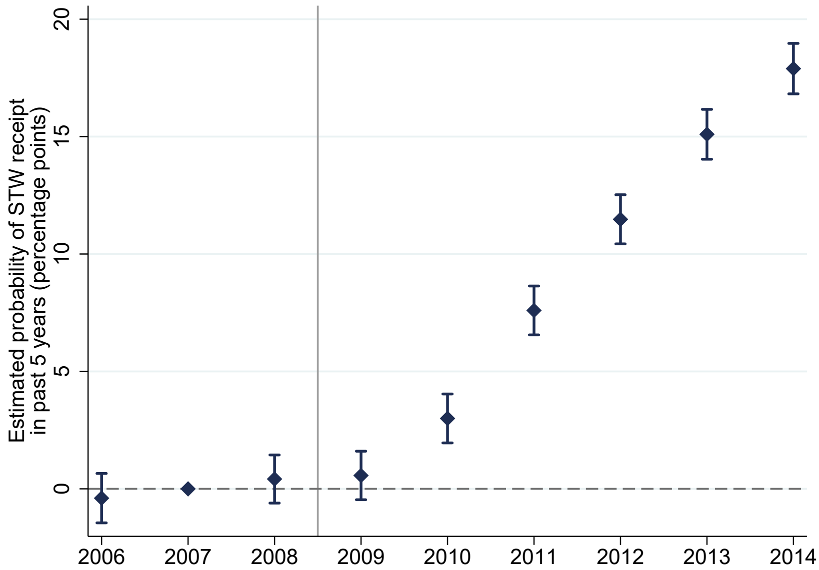
$$
\beta_{2009}^{RF} = \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}} \tag{2}
$$

$$
\beta_{2010}^{RF} = \beta_0^{TOT} \cdot \frac{\mathrm{d}T_{2010}}{\mathrm{d}Z_{2009}} + \beta_1^{TOT} \cdot \frac{\mathrm{d}T_{2009}}{\mathrm{d}Z_{2009}} \tag{3}
$$

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 $\widehat{\beta}_t^{RF}$ and the recursive structure of equations (2), (3), etc., we can identify the sequence of dynamic treatment effects $\{\beta_0^{TOT}, \beta_1^{TOT}, ..., \beta_k^{TOT}\}$.

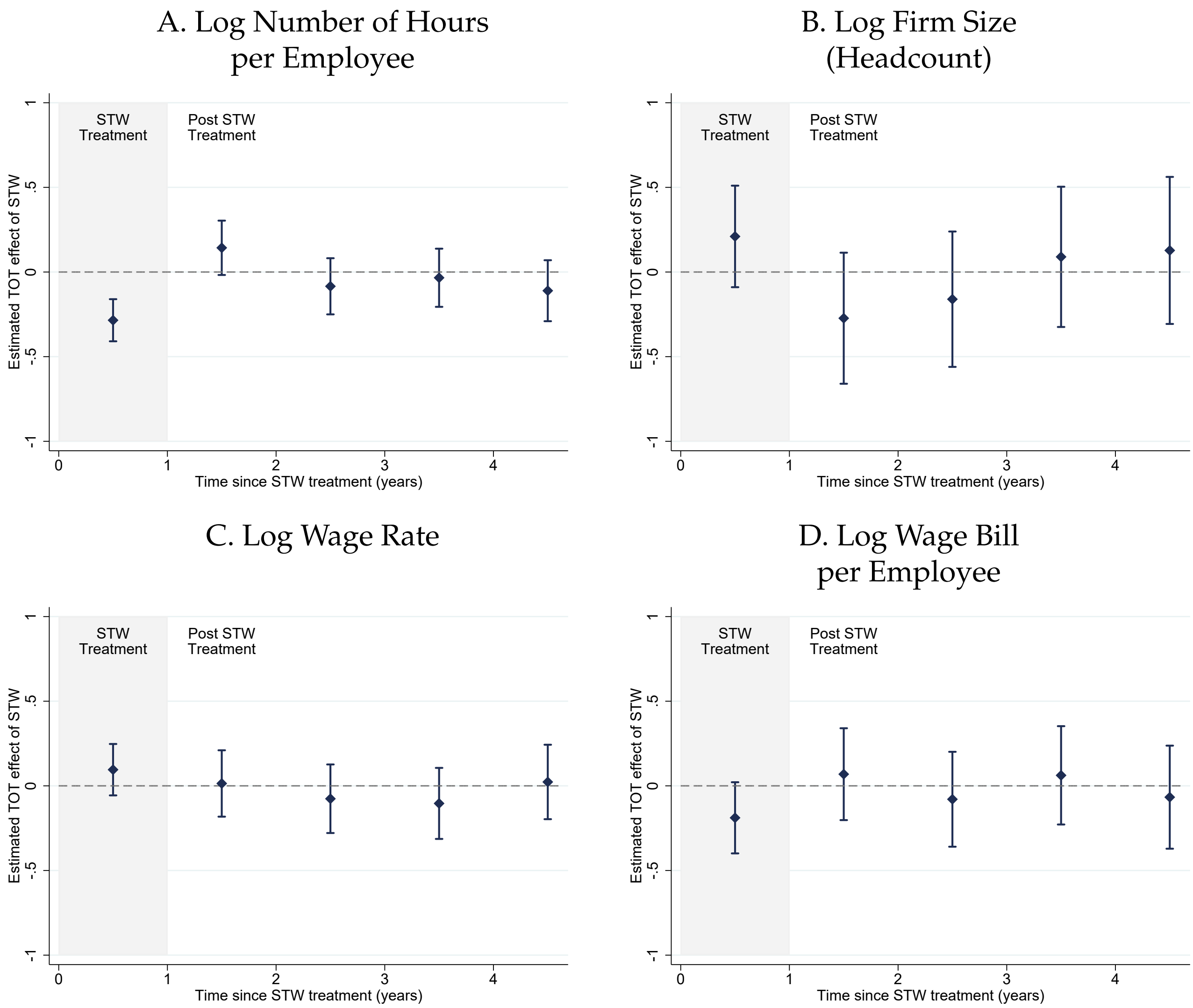
We display in Appendix Figure C-4 the results of these dynamic TOT effects, for various outcomes. The results suggest that the effects are large on impact, but disappear immediately once treatment stops.

Figure C-3: EFFECT OF INPS CODE AND FIRM SIZE INTERACTION ON THE PROBABILITY OF HAVING RECEIVED SHORT TIME WORK IN THE PAST 5 YEARS



Notes: The graph reports the coefficients $\widehat{\gamma}_1^t$ estimated from equation (1) for all years $t \in [2006, 2014]$ using as outcome the firm-level probability of having received STW in the previous five years. The omitted year is 2007, so all results are relative to 2007. The vertical bars indicate 95% confidence intervals based on standard errors clustered at the INPS code times firm size group level.

Figure C-4: TOT Estimates of the Dynamic Effects of Short Time Work



Notes: The graphs report the coefficients $\widehat{\beta}_k^{TOT}$ for $k \in [0, ..., 4]$ for the dynamic effects of STW treatment on various outcomes. These effects are estimated recursively as illustrated in Appendix C.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. The wage rate is defined as total earnings per hour worked per employee.

C.3 Event Studies for Worker-Level Outcomes

Identification of Dynamic Treatment Effects. We want to understand to what extent the dynamic patterns from the event studies reveal the causal dynamic impact of STW treatment. Endogeneity concerns prevent interpreting the event study estimates on the treated as the causal dynamic impact of STW. 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 two things that can be done to tackle them.

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. This outcome depends on some observed and unobserved individual characteristics η_i and X_{it}, and 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 ($\varepsilon_{j,t}$). Such shocks 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 badly 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 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.

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

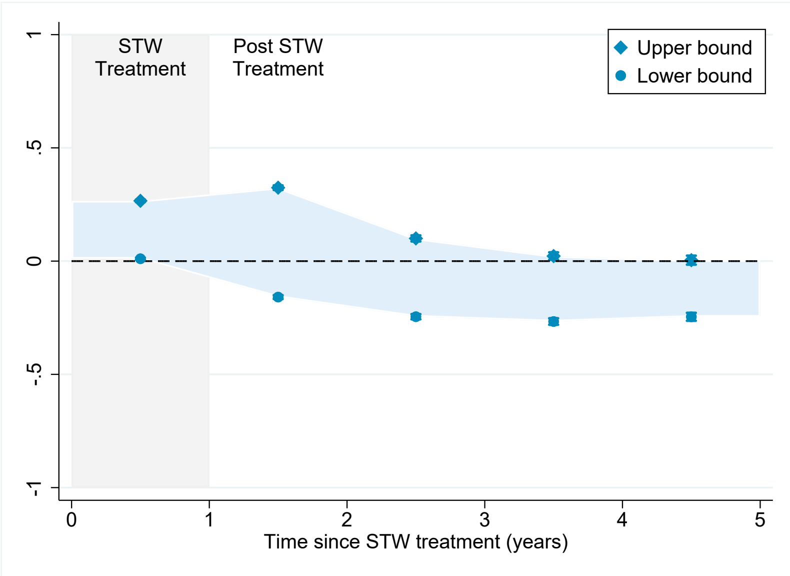
Counterfactual 1: A similar worker at time $t-1$ from any non-eligible firm due to firm size and INPS code. Under the assumption that only the worse shocks select into STW, that is $\mathbf{E}[\varepsilon_{j,t+k} + \mu_{i,t+k} | \text{Counterfact 1}] \geq \mathbf{E}[\varepsilon_{j,t+k} + \mu_{i,t+k} | \text{STW Treated}]$, the outcomes for workers in this first 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 difference $\beta_k^T - \beta_k^{C1}$ 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: A similar worker at time $t-1$ from non-eligible firms due to firm size and INPS code, who experiences a layoff in t. If we assume that the shock triggering a layoff is at least as bad as a STW shock and that the firms would have used STW instead if they were eligible, that is $\mathbf{E}[\varepsilon_{j,t+k} + \mu_{i,t+k} | \text{Counterfact 1}] \leq \mathbf{E}[\varepsilon_{j,t+k} + \mu_{i,t+k} | \text{STW Treated}]$, then workers in this layoff comparison group can be thought as a lower bound counterfactual for what would have happened to treated workers absent STW. As we show in Section 3.2, this assumption is credible as 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 the previous assumption, the difference $\beta_k^T - \beta_k^{C2}$ 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.

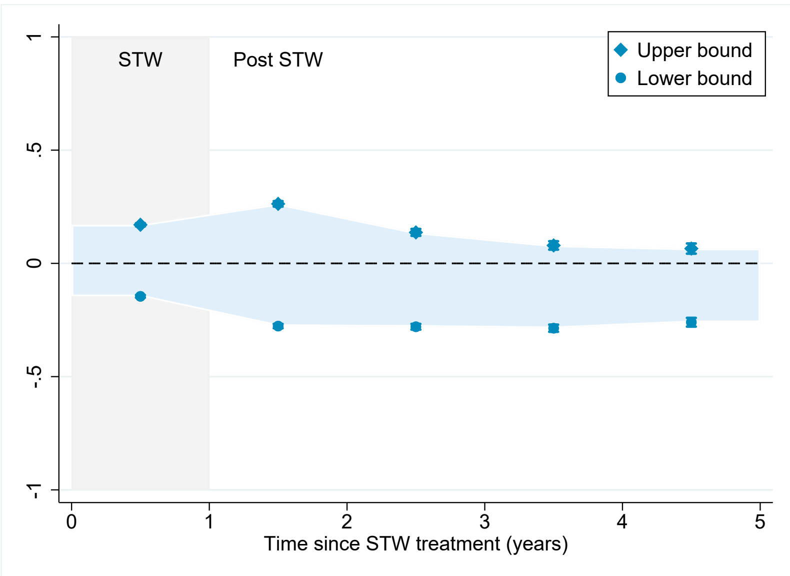
In Appendix Figure C-5, we overlay the upper bound and lower bound estimates from the event study approach. In Panel A, we show the effect for employment, and in Panel B the effect on worker's total gross earnings plus transfers. The graphs show that, in both cases, the upper bound estimate – which compares 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 8.

Figure C-5: Dynamic Effects of Short Time Work on Workers' Outcomes

A. Probability of Employment



B. Earnings + CIGS/Transfers



Notes: The graphs report bounds on the dynamic treatment effect of STW receipt on workers' employment probability and total earnings including social insurance transfers and STW. The shaded area shows upper- and lower-bound estimates of the dynamic effect, using the event study estimates reported Panel A and C of Figure 8. The upper bound (indicated by diamonds) compares treated individuals with the layoff counterfactual. The lower bound (indicated by circles) compares treated workers with workers in non-eligible firms.

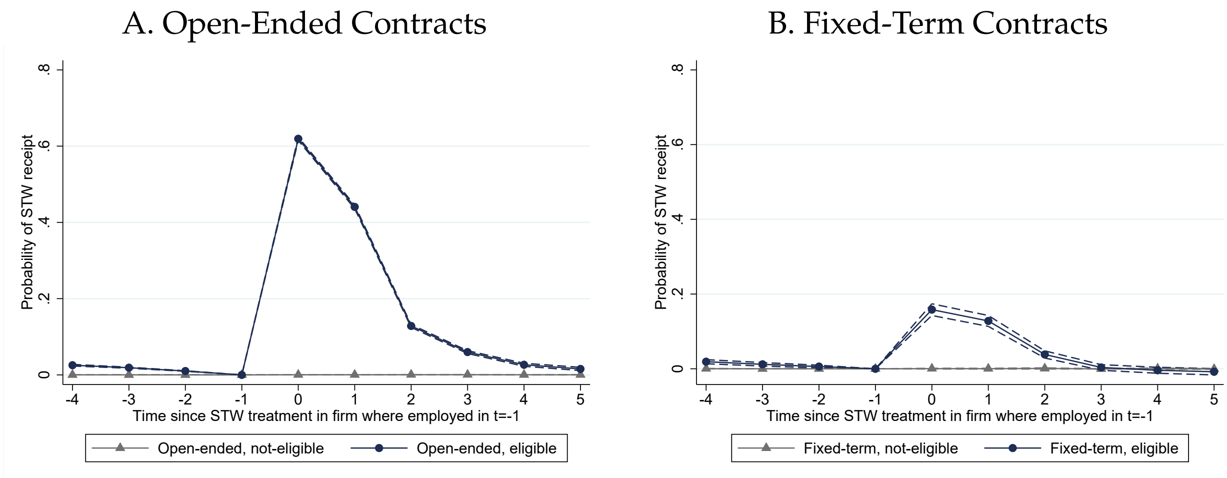
Accounting for Firm-level Shocks Using Variation in Treatment by Contract Type. A second way in which we can address concerns related to the correlation between STW treatment and persistent firm-level shocks is by using variation in STW exposure between workers on open-ended and fixed-term contracts within the same firm. This allows us to control for firm fixed effects and thus improve on our identification of the dynamic effects of STW on workers' careers.

Appendix Figure C-6 shows the probability of STW receipt for workers around the time when a firm experiences a STW event. In Panel A we focus on workers who are on open-ended contracts, while in Panel B on workers who are on temporary contracts in the year before the event. In both panels, we also report the evolution of the probability of STW receipt among a control group of workers who have similar observable characteristics but work in firms that are not eligible for STW at time $t = -1$. The figure shows very clearly that the probability of STW take-up is much larger among workers on open-ended contracts than among workers on temporary contracts, conditional on the firm going into STW. This is in line with the theoretical predictions – discussed at the end of Section 2.1 – whereby firms have incentives to put open-ended-contract workers (but not temporary-contract workers) on STW.

The main advantage of using variation in access to STW between temporary versus open-ended contracts within the same firm is that it allows to fully control for firm-level shocks $\varepsilon_{j,t+k}$. Yet, variation in $T_{jt} = 1$ will now be driven by the nature of the contract individuals had at time t, which may be correlated with $\mu_{i,t+k}$ as individuals on temporary versus open-ended contracts have different labor market dynamics in general. We can nevertheless control for these differences in workers' dynamics absent STW by comparing workers in open-ended contracts versus workers in temporary contracts in non-eligible firms that did not experience STW in time t.

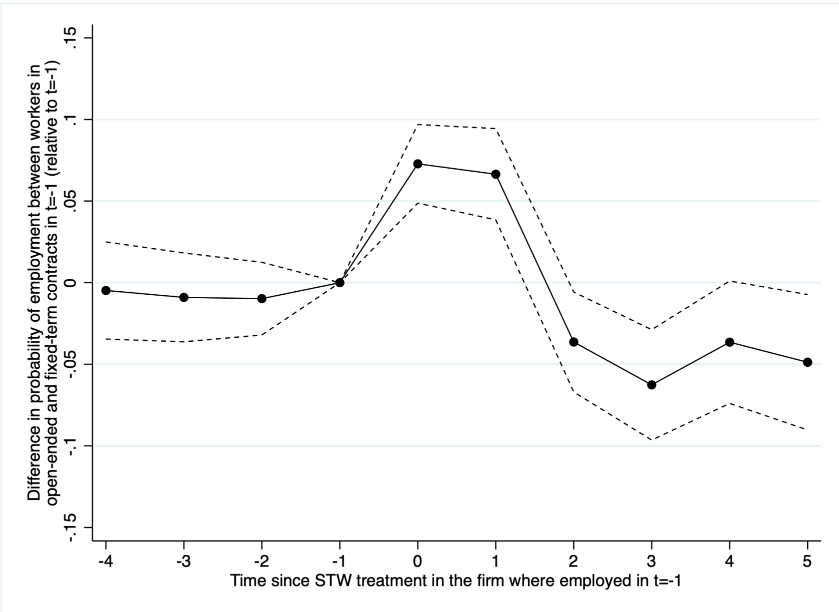
We report in Appendix Figure C-7 below the evolution of the differential probability of employment of workers employed in open-ended versus fixed-term contracts in event time -1 in firms experiencing a STW event for the first time at event time 0, relative to similar workers in non-eligible firms. The figure shows clear positive effects of STW on worker's employment in the short run, but these effects dissipate entirely after STW exhaustion. These results provide strong, transparent and complementary evidence on the dynamic effects of STW, confirming that STW had positive effects in the short run, but that these effects did not last.

Figure C-6: PROBABILITY OF SHORT TIME WORK RECEIPT BY CONTRACT TYPE



Notes: The graphs report the estimated coefficients of event study regressions for the probability of STW receipt at the worker level, for workers on different contract types and different event-year definitions. All estimates are relative to event-year -1. 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. The treatment group (indicated by solid circles) consists of workers who, at event time $t = -1$, were employed in eligible firms that experienced their first STW spell in $t = 0$. In other words, for the treatment group, an event year is defined as the first year in which the firm where the worker was employed in $t = -1$ experiences a STW event, conditional on said firm to be eligible for STW at event time -1. We consider eligible firms with FTE size $\in (15; 25]$ in $t = -1$ in our sample. We distinguish two groups of treated workers: those employed under an open-ended contract in -1 (Panel A), and those employed under a fixed-term contract in -1 (Panel B). For each of these two treatment groups, we define a comparison group. The comparison group (indicated by solid triangles) consists of workers employed at non-eligible firms with 6-month average FTE size $\in (15; 25]$ at event time -1. Individuals in the comparison group are matched to individuals in the treatment group using Mahalanobis nearest-neighbor matching without replacement based on gender, age, job characteristics (including contract type) 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. The probability of STW received is measured unconditional on employment in the same firm as $t = -1$ and unconditional on employment.

Figure C-7: DYNAMIC EFFECT OF SHORT TIME WORK RECEIPT ON THE PROBABILITY OF EMPLOYMENT: USING CONTRACT TYPE AS SOURCE OF WITHIN-FIRM VARIATION IN EXPOSURE TO STW



Notes: The graph reports the evolution of the differential probability of employment of workers employed in open-ended versus fixed-term contracts in $t = -1$ in firms experiencing a STW event for the first time in $t = 0$. More precisely, each dot reports the coefficient estimates of a regression of the employment probability on the full set of interactions between contract type, treatment/comparison status (as defined in the notes to Figure C-6) and event time, conditional on individual fixed effects. Estimates are relative to $t = -1$. The dashed lines around the estimates indicate 95% confidence intervals based on robust standard errors clustered at the individual level.

C.4 Heterogeneous Treatment Effects by Temporariness of the Shock

We are interested in understanding how the treatment effects of STW depend on the persistence of the shock experienced by firms. To this end, we start by deriving a data-driven characterization of industries and local labor markets (LLM) that have experienced more or less permanent shocks. We then document heterogeneity in the long-run effects of STW by the temporariness of the shock.

We start by constructing panels of total employment counts in each year at the LLM or 3-digit industry level, using data on non-eligible firms, irrespective of firm size. For each panel separately, we estimate regressions of the following form

$$\Delta \log e_{j,2007-2014} = \alpha_S + \beta_S \Delta \log e_{j,2007-2009} + \varepsilon_j \tag{4}$$

where $\Delta \log e_{j,2007-2014}$ is the change in the logarithm of total employment in LLM or industry j between 2007 and 2014, $\Delta \log e_{j,2007-2009}$ is a similar change between 2007 and 2009, and ε_j is an error term. The coefficient β_S captures the average correlation between short-run and long-run employment growth: in other words it measures the average magnitude of the shock in employment due to the double-dip recession between 2009 and 2014, expressed as the extent of the deviation from pre-crisis employment growth. Having estimated model (4), we rank LLMs/industries into quantiles of the distribution of the residuals, with more negative values of the residual term indicating more persistent shocks. Here we exploit the notion that the residual term should be positive for LLMs/industries in which the shock is relatively more temporary/less permanent, and negative for LLMs/industries in which it is more persistent.

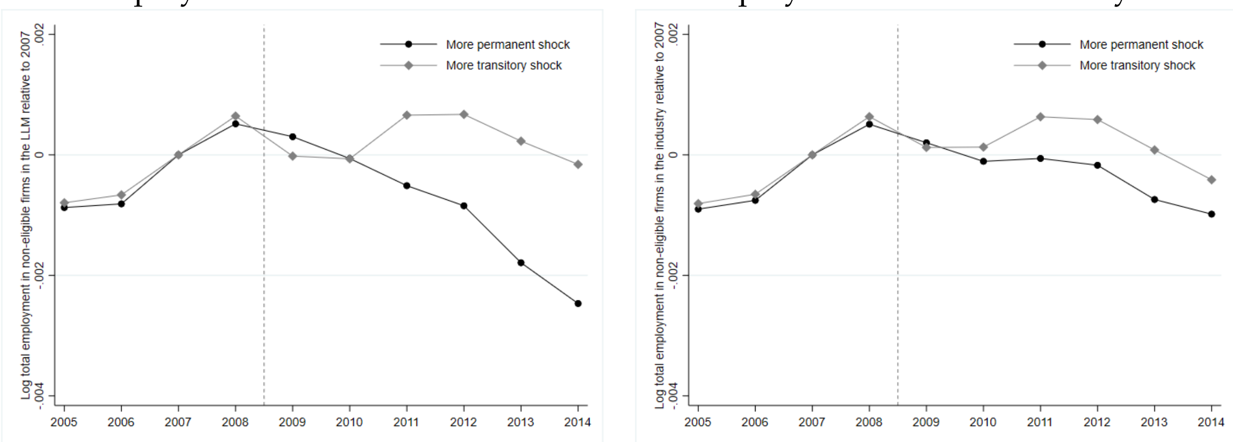
Note that we estimate model (4) and rank LLMs/industries using the sample of non-eligible firms (but then extend the ranking to both eligible and non-eligible firms). Also, when running the regression at the LLM level, we control for the fraction of workers eligible for STW in the LLM in pre-recession years to account for any spillover effect of STW take-up between eligible and non-eligible firms. This ensures that we measure the transitoriness of the shock on sectoral or LLM employment in the absence of STW.

Appendix Figure C-8 shows the evolution of the logarithm of total employment in non-eligible firms at the LLM (Panel A) and industry (Panel B) level relative to 2007, distinguishing between LLMs/industries with predicted residuals above and below the median level, i.e. with a more transitory and permanent employment shock respectively. The graphs provide supporting evidence for our proposed approach to identify employment shocks of different persistence. It shows that LLMs (industries) that we classify as subject to more transitory shocks experienced a similar decline at the onset of the Great Recession compared to LLMs (industries) that we classify as subject to more persistent shocks; but the former LLMs (industries) recovered starting in 2010, while the latter remained persistently affected.

We then use the above dichotomization to investigate whether STW take-up and treatment effects are heterogeneous with respect to the temporariness of the shock. To this effect, we run models based on specification (5) and (6). The results are reported in Appendix Table C-1, where we consider any CIG take-up as treatment. Panel A shows heterogeneity with respect to the temporariness of the shock at the LLM level, Panel B at the industry level. Estimates in both panels indicate that, when the shock is more temporary, firms take up STW more and the employment effects of STW are larger. The magnitude of the effects is qualitatively important and similar across the two estimation, but estimated with not enough precision to be significant at conventional levels. The effect on hours per employee (conditional on employment) does not appear to be heterogeneous by type of shock.

Figure C-8: Evolution of Log Employment by Temporariness of the Employment Shock at the LLM and Industry Level

A. Employment Shock at LLM Level   B. Employment Shock at Industry Level



Notes: Each panel reports the evolution of log employment counts at the LLM (Panel A) or 3-digit industry (Panel B) level, relative to 2007. LLMs/Industries are split into two groups depending on whether the estimated residual from the estimation of model (4) $\hat{\varepsilon}_j = \Delta \log e_{j,2007-2014} - \hat{\alpha}_S - \hat{\beta}_S \Delta \log e_{j,2007-2009}$ falls above or below the median of the distribution of residuals among non-eligible firms.

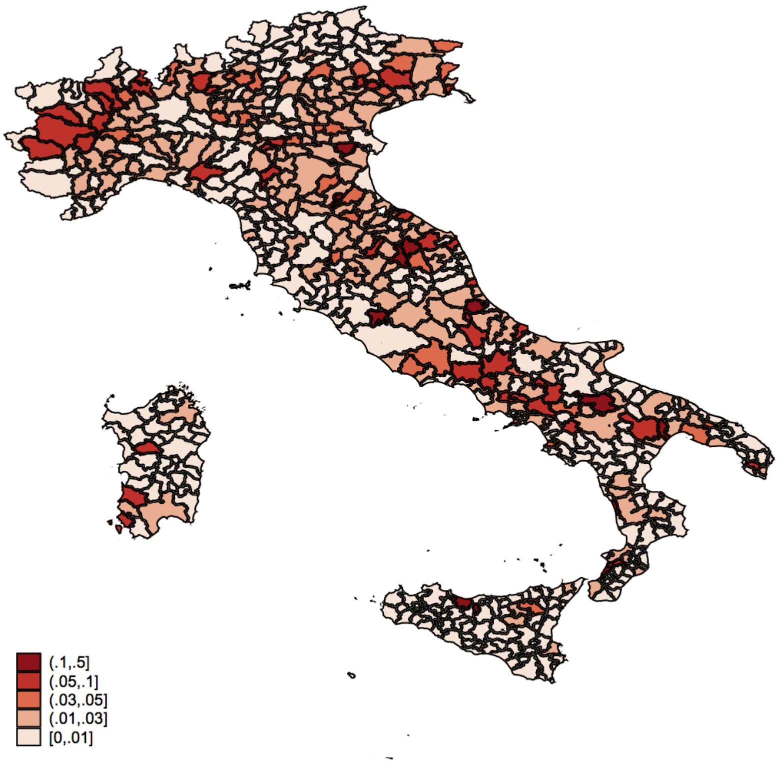
Table C-1: SELECTION OF FIRMS INTO SHORT TIME WORK (CIG) AND HETEROGENEOUS TREATMENT EFFECTS BY TEMPORARINESS OF THE EMPLOYMENT SHOCK

	Probability of CIG take-up (1)	Firm size headcount (inverse hyperbolic sine) (2)	Number of hours per employee (inverse hyperbolic sine) (3)
	A. Employment Shock at LLM Level		
$\mathbb{1}[N_{i,2008} > 15] \times \mathbb{1}[g \in \mathcal{E}]$	.061***		
	(.009)		
$\mathbb{1}[N_{i,2008} > 15] \times \mathbb{1}[g \in \mathcal{E}] \times$ Tempor.	.025**		
	(.012)		
$CIG^{2014-2010}$		.038	-.344*
		(.317)	(.176)
$CIG^{2014-2010} \times$ Tempor.		.367	.064
		(.359)	(.199)
	B. Employment Shock at Industry Level		
$\mathbb{1}[N_{i,2008} > 15] \times \mathbb{1}[g \in \mathcal{E}]$	.060***		
	(.009)		
$\mathbb{1}[N_{i,2008} > 15] \times \mathbb{1}[g \in \mathcal{E}] \times$ Tempor.	.032***		
	(.012)		
$CIG^{2014-2010}$		.062	-.315**
		(.300)	(.155)
$CIG^{2014-2010} \times$ Tempor.		.427	-.002
		(.349)	(.180)
Obs.	300795	300795	300795

Notes: Column 1 reports the estimates of the coefficient $\widehat{\lambda}_1$ and its associated cluster-robust standard error in parenthesis from an augmented version of specification (6) in which we include interaction terms with a dummy for whether the firm is in an LLM/industry in which the employment shock is estimated to be temporary. Columns 2-3 report the $\widehat{\theta}_{IV}$ coefficients estimated from a similarly augmented version of equation (5) and their associated cluster-robust standard errors in parenthesis for a set of different firm-level outcomes. Panel A shows heterogeneity with respect to the temporariness of the shock at the LLM level, Panel B at the industry level. In this table, we include any type of CIG under STW treatment.

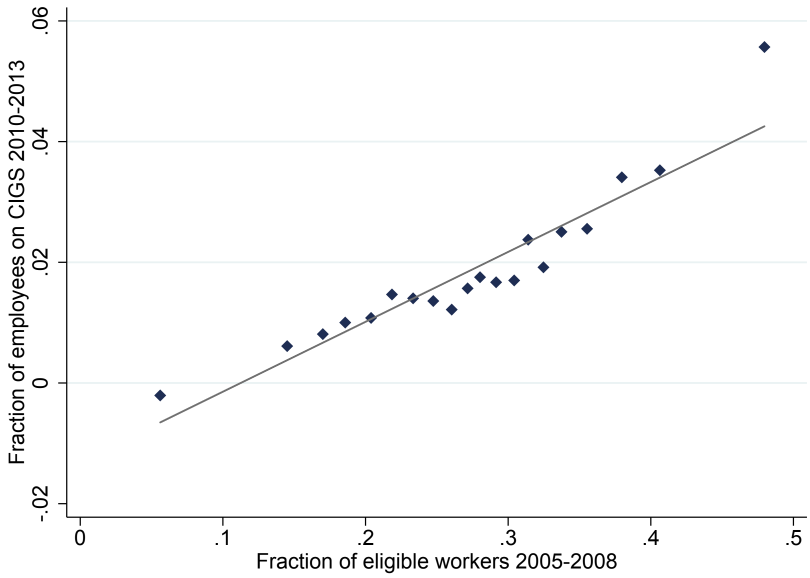
D Selection & Spillover Effects - Additional Evidence

Figure D-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 (LLMs), as defined by the Italian Statistical Institute (ISTAT). The graph reports the fraction of workers treated by CIGS in the years 2010 to 2013 in each 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 D-2: FRACTION OF WORKERS ELIGIBLE FOR CIGS IN AN LLM BASED ON FIRM SIZE AND INPS CODES DURING THE PRE-RECESSION PERIOD VERSUS FRACTION OF WORKERS ON CIGS DURING THE RECESSION



Notes: The graph reports a binned scatter plot of the relationship between the fraction of employees on STW in 2010-2013 (y-axis) and the fraction of workers eligible for STW in 2005-2008, based on the interaction between firm size and INPS codes in the LLM (x-axis). Both variables are measured at the LLM level, and are residualized on firm-level and LLM-level controls (see Section 5.3 for details). This relationship corresponds to the first stage of IV model (9).

E Model Calibration & Counterfactual Analysis

We develop a matching model of the Italian labor market to calibrate the reallocation effects of STW during the Great Recession, using our reduced-form evidence. There are two types of firms in the model, that differ by their level of productivity. We model the Italian economy in the period 2009-2014 as being in a steady-state. This captures the fact that the recession in Italy was persistent. In this context, we wish to ask quantitatively how the presence of STW for low productivity firms affected equilibrium TFP and the allocation of employment in that steady-state.

The way STW enters the model is that workers in low productivity firms can get a subsidy for hours not worked below a threshold. This endogenously reduces equilibrium hours per worker in low productivity firms, and increases the employment level of these firms. By increasing labor market tightness, this reduces the equilibrium employment of high productivity firms. This captures in a nutshell the logic of the reallocation effects of STW.

The contribution of this calibration is to use our reduced-form evidence to identify the key parameters of the model, and therefore provide a quantitative exploration of the effects of STW. We identify for instance key parameters of the matching function from our quasi-experimental evidence on reallocation. We also identify key parameters of firms' production function from our reduced-form evidence on the causal effects of STW.

This section 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 exercises.

E.1 Matching in the Labor Market

We consider a unit mass of workers in a frictional labor market. 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 sufficient statistic for both the vacancy filling probability $q(\theta)$ and the job finding probability $\phi(\theta)$. Each period, a fraction δ of existing employment relationships is destroyed exogenously.[1]

[1] We note that this assumption, which greatly improves the tractability of the model, implies that the reallocation impact of STW will operate only through the job creation channel in the model. In practice, our results in Table 1 shows that among firms taking up STW, headcount employment increases both through a relative increase in inflows and a relative decrease in outflows.

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.

Identifying Parameters of the Matching Function from Reduced-Form Evidence. We consider the Cobb-Douglas matching function:

$$M(u_t, v_t) = \mu u_t^{\gamma} v_t^{1-\gamma} \tag{5}$$

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

$$q(\theta_t) = \frac{M(u_t, v_t)}{v_t} = \mu \left(\frac{u_t}{v_t}\right)^{\gamma} = \mu \theta_t^{-\gamma} \tag{6}$$

Log linearizing the above equation yields:

$$\ln(\frac{M}{v_t}) = \ln(\mu) - \gamma ln(\theta) \tag{7}$$

To obtain information on the measures of hires per vacancy, M/v_t, and labor market tightness at the local labor market level, θ, we use the RIL 2007, 2010 and 2015 surveys from INAPP. Using questions on the number of new hires that the firm would currently like to hire, 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.[2]

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:

$$v_{j,t} = \frac{n_{j,t}}{n_{j,t}^{RIL}} \cdot v_{j,t}^{RIL} \tag{8}$$

Once a measure of vacancies $v_{j,t}$ is obtained, this is combined with measures of matches $M_{j,t}$ and of unemployment $u_{j,t}$ 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 ISTAT.

We therefore can run the following specification:

[2] The questions that we use are question C7 for 2010 and question C8 for 2015. Both are phrased in the same way and ask the firm how many employees it is currently trying to recruit (Quanti dipendenti sta attualmente cercando l'impresa?).

$$\log q_{j,t} = a + b\log(\theta_{j,t}) + c_j + \zeta_t + \nu_{j,t} \tag{9}$$

For b to identify $-\gamma$, exogenous variation in $\theta_{j,t}$ is required. We use exposure to CIGS treatment as an instrument. Intuitively, the intensity of CIGS treatment offers an exogenous shock to labor demand in the LLM as depicted in Panel C of Appendix Figure E-1. 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:

$$\Delta\log q_{j,t} = b\Delta\widehat{\log(\theta_{j,t})} + W_j'\mu_1 + \zeta_t + \nu_{j,t} \tag{10}$$

$$\Delta\log(\theta_{j,t}) = Z_j^{2005-2008} + W_j'\mu_0 + \mu_{j,t}$$

where Δ is the difference operator between pre versus post 2008.[3] Z_j is the average yearly fraction of workers in 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. W_j is a vector of LLM characteristics that could be correlated with the fraction of treated workers and likely to affect equilibrium labor market 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 LLMs 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. From this specification, we obtain $\gamma = .53$.

E.2 Firms

Firms produce a homogeneous consumption good using labor inputs according to the technology $\epsilon_k F(h_t, n_t)$. Firms differ in terms of their productivity ϵ_k, which can take two levels: ϵ_H for high productivity firms, and ϵ_L for low productivity firms. We consider these two productivity levels as persistent characteristics of firms, to capture the issue of reallocation created by STW in an environment where a recession creates a persistent negative shock for certain firms. The production function depends on the number of employees n and the number of hours worked per employee h.

[3]Because only three waves of the survey are available (2007, 2010 and 2015), the pre-2008 data is observations for 2007, and post-2008 data is an average of the 2010 and 2015 observations.

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

$$\Pi(n_{t-1}) = \max_{v_t}\{\epsilon_k F(h_t, n_t) - wh_t n_t - cv_t + \beta\Pi(n_t)\} \tag{11}$$

subject to the law of motion of employment:

$$n_t = (1-\delta)\cdot n_{t-1} + q(\theta_t)\cdot v_t \tag{12}$$

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

In a stationary equilibrium, $\theta_t = \theta_{t+1} = \theta$, so the first-order condition of the firm reduces to:

$$\epsilon_k F_n'(h_t, n_t) = wh_t + (1-\beta(1-\delta))\frac{c}{q(\theta)} \tag{13}$$

E.2.1 Identifying Production Function Parameters

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

$$F(h_t, n_t) = h_t^{\alpha} n_t^{\eta} \tag{14}$$

We then use our reduced-form evidence to identify the parameters α and η of the production function. Log-linearization of the first order condition of the firm's profit maximization with respect to employment gives:

$$\log n = \frac{\alpha}{1-\eta}\log h - \frac{1}{1-\eta}\log(wh) - \frac{1-\beta(1-\delta)}{1-\eta}\frac{c}{whq(\theta)} + \frac{1}{1-\eta}\log(\epsilon_k\eta) \tag{15}$$

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

$$\log n = \frac{\alpha-1}{1-\eta}\log h - \frac{1}{1-\eta}\log w - \frac{1-\beta(1-\delta)}{1-\eta}\frac{c}{whq(\theta)} + \nu_k \tag{16}$$

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 $W = wh$. After 2015, the introduction of $\tau_f > 0$ for firms on CIGS introduces some exogenous variation in the wage bill.[4] The new

[4] In September 2015, a reform of the Italian *Cassa Integrazione Guadagni* introduced a degree of progressivity in the experience-rating component of STW (D. Lgs. 148/2015). Before the reform, firms using STW had to pay a contribution equivalent to 3% (or 4.5% for firms with more than 50 employees) of the subsidy received by their workers. After the 2015 reform, these rates have been increased to 9% of the wage bill corresponding to hours not worked. The 9% rate applies to the first 52 weeks of subsidy, and is then increased to 12% for the next 52 weeks and to 15% for any additional week.

specification becomes:

$$\log n = \frac{\alpha}{1-\eta}\log h - \frac{1}{1-\eta}\log W - \frac{1-\beta(1-\delta)}{1-\eta}\frac{c}{W\cdot q(\theta)} + \nu_k \tag{17}$$

The previous log-linearization 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 LLMs. Structurally, the coefficients α_1, α_2 and α_3 from this regression 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 $\alpha = .6, \eta = .7$.

E.2.2 Firm Productivity

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

We observe that 13% of firms are treated post 2009 in the baseline DD sample. We thus define the fraction of high productivity firms $\rho = .87$. Further, taking the mean (log) total factor productivity of these firms, and normalizing the low productivity value to 1 yields: $\epsilon_L = 1, \epsilon_H = 1.62$.

E.3 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 the same rate β as firms do. Since 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 hour 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 employed by a firm of productivity $\epsilon_k \in \{\epsilon_H, \epsilon_L\}$ is W_k^e:

$$W_k^e = u(c_k, h_k) + \beta(\delta W^u + (1-\delta)W_k^e) \tag{18}$$

In the steady state, a constant proportion of workers are employed by the low versus high productivity firms and, similarly, a constant proportion of vacancies are created by the low productivity firms v_L versus the high productivity firms $1 - v_L$.

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

$$W^u = u(b, 0) + \beta(\phi(v_L W_L^e + (1-v_L)W_H^e) + (1-\phi)W^u) \tag{19}$$

The continuation value of being employed in a firm of productivity ϵ_k must be 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 reservation 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.

Calibration of Utility Function. We use the following isoelastic, additively separable utility function:

$$u(c, h) = \frac{c^{1-\sigma_c} - 1}{1 - \sigma_c} - \varphi \frac{h^{1+\sigma_h}}{1 + \sigma_h} \tag{20}$$

where 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 labor supply elasticity. We set this parameter to $\sigma_h = 3.5$ in line with conventional calibrations from New Keynesian models (see Galí [2011]).

E.4 Wage and Hours Determination

We assume wages are rigid and not bargained over, to be in line with the Italian context which puts institutional constraints on the rebargaining of wages as explained in the main text. We capture the presence of wage rigidity in the data by assuming that the wage has the following form:

$$w(\epsilon) = w_s \epsilon^{w_a} \tag{21}$$

with $w_a < 1$. The wage 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 .2, in line with similar models in the literature (see Landais, Michaillat and Saez [2018]).

Hours in low productivity firms are 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, to make the model simple and to capture the presence of hours rigidity, we consider a simple exogenous hours schedule:

$$h(\theta, \epsilon) = h_s \epsilon^{h_a} \theta^{h_b} \tag{22}$$

To estimate the parameter h_b – the responsiveness of the hours function to a change in labor market tightness – we regress log hours among ineligible firms at LLM level against log tightness, instrumented by eligibility of CIGS. This model obtains a coefficient of .14.

E.5 Additional Parameters

E.5.1 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 CIGS. 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.

E.5.2 Miscellaneous Parameters

The model imposes an exogenous separation rate, δ. To calibrate the separation rate we compute the probability that an individual working in a firm in year t will still be working with the same firm in $t+1$, accounting for all types of employment contracts. We find an annual separation rate of .2. The model's discount factor, β, is set to .935, implying an annual interest rate of 7%.

E.6 Summary of Exogenous Parameters

The model is run at yearly frequency. All parameters in the following table are yearly unless otherwise specified.

Parameter	Description	Calibrated value
β	Discount factor	.935
α	Hour share	.6
η	Labor share	.7
γ	Matching function curvature	.53
w_a	Wage function curvature	.2
$\bar{h}$	Total weekly hours endowment	40
δ	Separation rate	.2
b	Unemployment benefit	$.7 \cdot \bar{h} \cdot w_s$
τ	STW replacement rate	.8
σ_c	Coefficient of risk aversion	2.5
σ_h	Inverse of Frisch elasticity of labor supply	3.5
ρ	Fraction of high productivity firms	.87
ϵ	Productivity values	$\{1; 1.62\}$

E.7 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 labor scaling
h_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	.108
High productivity weekly hours level	34
Low productivity weekly hours level, without STW	39
Low productivity weekly hours level, with STW	20
Proportion of total employment that is high productivity	.9

The target unemployment rate is the Italian unemployment rate computed from the ISTAT data. We target the average unemployment rate in the period 2008-2014: .108. Low productivity firms are defined as:

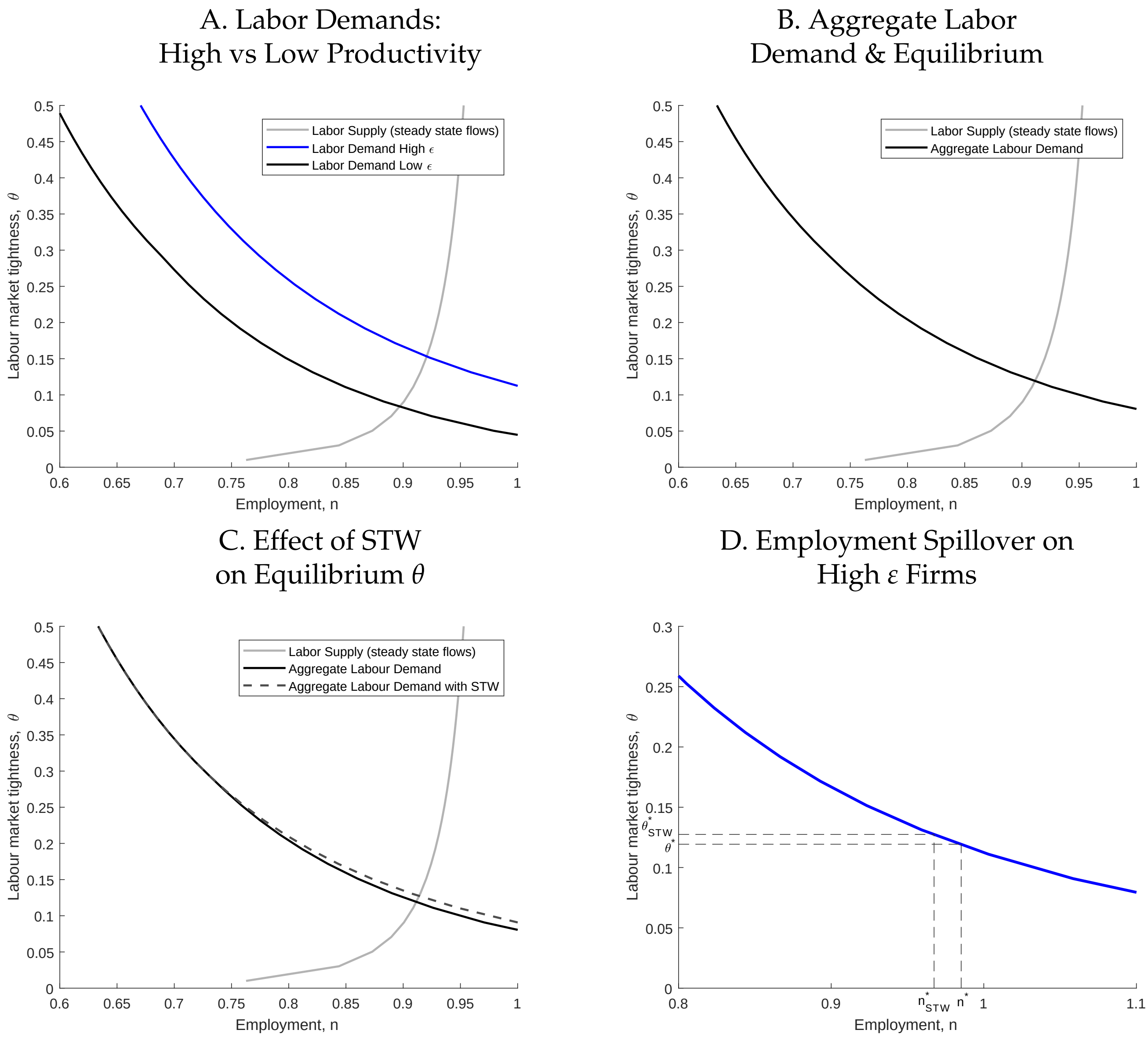
- For eligible firms, those that take up CIGS
- For non-eligible firms, in eligible 5-digit industries, firms whose total factor productivity is in the bottom 12% of the distribution, post 2009

E.8 Equilibrium & Spillover Effects

A steady state equilibrium consists in a set of: (i) hours levels h and wage levels 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 maximize 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 Appendix Figure E-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 $n^d(\theta)$, which is a decreasing function of θ as the marginal product of n is decreasing (Panel A). With random matching, aggregate labor demand is simply the weighted sum of demands of high and low productivity firms. Equilibrium tightness 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 not 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 production technology is in n (Panel D).

Figure E-1: EQUILIBRIUM REPRESENTATION & SPILLOVER EFFECTS OF SHORT TIME WORK



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 $n^d(\theta)$, which is a decreasing function of θ in the $\{n, \theta\}$ space. With random matching, aggregate labor demand is simply the weighted sum of demands of high and low productivity firms (Panel A). Equilibrium tightness 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 not 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).

E.9 Counterfactual Policy Analysis

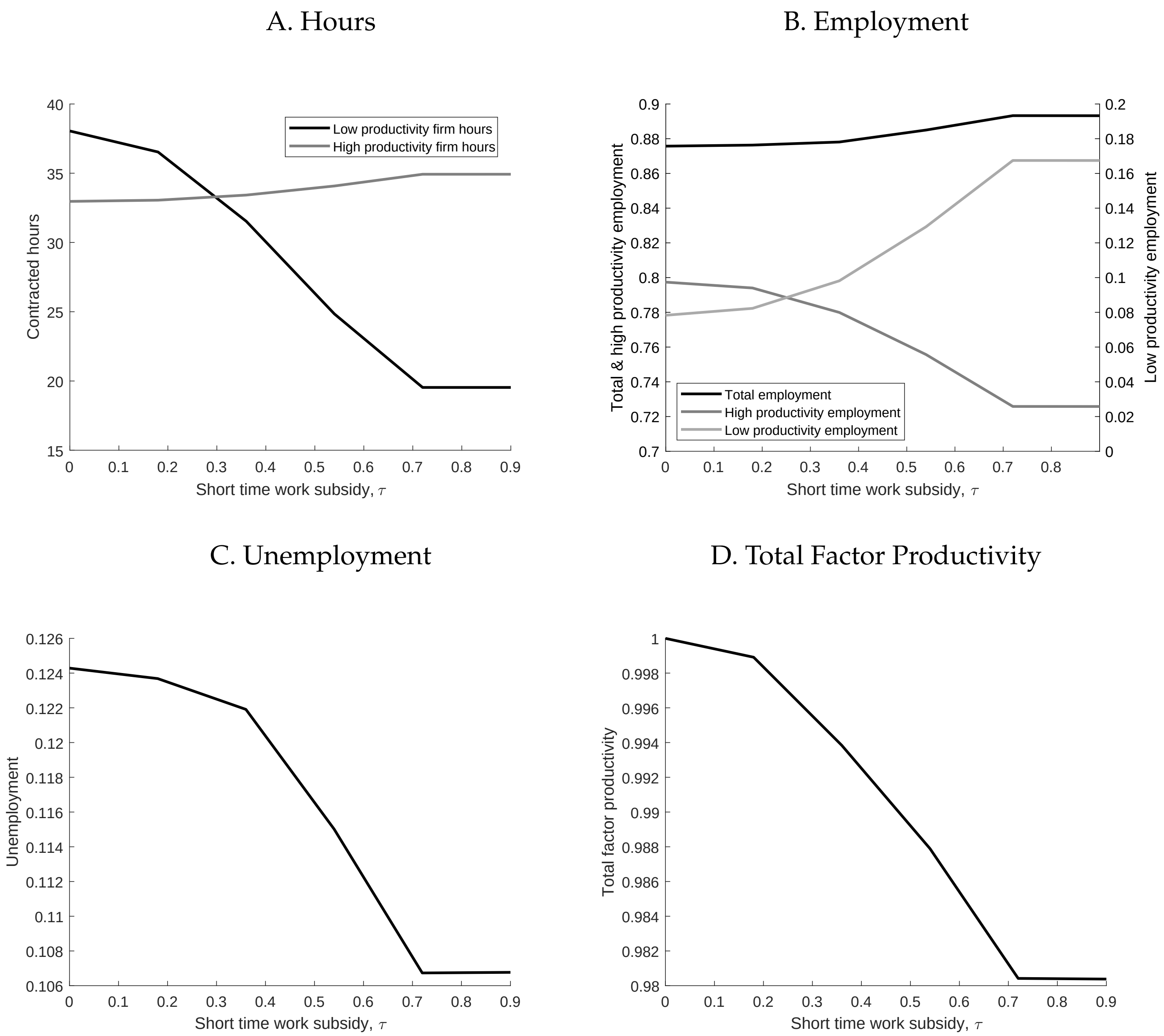
Our calibration relies on the thought experiment that we have a version of the Italian economy where all firms correspond to firms above 15 FTE and are eligible to STW. We use this model to explore how different levels of STW generosity would affect the equilibrium allocation in the labor market. In particular, this helps us to assess the counterfactual scenario of what the level of employment and productivity would have been absent STW (i.e. $\tau = 0$) during the recession.

Appendix Figure E-2 displays the results of this counterfactual analysis of the steady state equilibrium during the recession, for various levels of the STW subsidy τ. Panel A shows that STW makes low productivity firms offer lower hours to workers. The level of hours in low productivity firms, for current levels of STW generosity, is 44% lower compared to the counterfactual of no STW. This matches closely our reduced-form estimates. Panel B shows the level of employment in high productivity firms (left axis) and in low productivity firms (right axis). The higher the generosity of STW, the higher the level of employment in low productivity firms. Compared to a situation without STW, the level of employment in low productivity firms is higher by about 50%, which again closely matches our reduced form evidence. But this comes at the cost of reducing high productivity employment, from .8 to .72 of the labor force. Overall, the total effect on employment is positive, as shown by total employment in Panel B, as well as by Panel C which plots the unemployment rate as a function of the STW subsidy. In the absence of any STW subsidy ($\tau = 0$), our calibration suggests that the unemployment level would have been 1.8 percentage point higher during the recession. In Panel D, we ask how the effects of STW on the relative allocation of employment between high and low productivity firms translate into aggregate TFP in the economy. We find that – by increasing the relative employment of low productivity firms – the provision of STW does come at the cost of a decline in aggregate TFP of about 2%.

We note that results from Appendix Figure E-2 also suggest that the marginal 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 A shows that, at $\tau = .8$, the hours constraint on low productivity firms does not bite any longer, so that any further increase in the subsidy does not affect the hours and employment allocation any more.

Finally, we note that computing the effects of STW on total welfare in this type of model is sensitive to the assumptions made on entry and profits. In our model, we do not have free entry, so there are firm profits, which we rebate lump sum to workers. In this environment we find that welfare is 2% higher with the current level of STW generosity than in an economy without STW.

Figure E-2: COUNTERFACTUAL SIMULATIONS: EFFECTS OF CHANGING SHORT TIME WORK GENEROSITY τ



Notes: The figure displays the 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 displays counterfactual values of hours per worker for low and high productivity firms. Panel B shows counterfactual values of total employment (left axis), and of employment in high productivity firms (left axis) and low productivity firms (right axis). Panel C shows counterfactual values of the equilibrium unemployment rate, and Panel D of total factor productivity. For Panel D, results are normalized to the level of TFP in the steady state equilibrium without STW (τ=0). All details of the calibration of the model are given in Appendices E.1-E.7.

References

Cellini Riegg, Stephanie, Fernando Ferreira, and Jesse Rothstein. 2010. "The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design." *Quarterly Journal of Economics*, 125(1): 215–261.

Galí, Jordi. 2011. "The Return of the Wage Phillips Curve." *Journal of the European Economic Association*, 9(3): 436–461.

Landais, Camille, Pascal Michaillat, and Emmanuel Saez. 2018. "A Macroeconomic Approach to Optimal Unemployment Insurance: Theory." *American Economic Journal: Economic Policy*, 10(2): 152–81.

Michaillat, Pascal. 2012. "Do Matching Frictions Explain Unemployment? Not in Bad Times." *American Economic Review*, 102(4): 1721–1750.