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Marlon R. Tracey
Southern Illinois University Edwardsville

Solomon W. Polachek
State University of New York at Binghamton and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Heterogeneous Layoff Effects of the US Short-Time Compensation Program*

The Short-Time Compensation (STC) program enables US firms to reduce work hours via pro-rated Unemployment Insurance (UI) benefits, rather than relying on layoffs as a cost-cutting tool. Despite the program's potential to preclude skill loss and rehiring/ retraining costs, firms' participation rates are still very low in response to economic downturns. Using firm-level UI administrative data, we show why by illustrating which type firms benefit from the program and which do not. Semiparametric estimation indicates STC reduces layoff rates for cyclically sensitive firms by about 15%, but has no effect for more cyclically stable firms.

JEL Classification: C21, C38, J63, J65

Keywords: short-time compensation, layoffs, inverse probability weighting, heterogeneity, finite mixture model

Corresponding author:
Solomon W. Polachek
Department of Economics
State University of New York at Binghamton
Binghamton, NY 13902
USA
E-mail: polachek@binghamton.edu

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1 Introduction

The US Short-Time Compensation (STC) program provides pro-rated benefits to employees who are forced to work reduced hours when demand temporarily slackens.[1] Benefits are paid from the state Unemployment Insurance (UI) trust fund, which are financed via the employer's payroll taxes. Firms taking advantage of this program are expected to retain potentially valuable workers, and as a result, local economies need not suffer from higher unemployment rates.[2] In light of the Great Recession in 2009, there has been a resurgence of interest in STC, with an additional 11 states enacting STC provisions, bringing the current total to 28 states. Yet, the participation rate of firms is still very low because they continue to rely on layoffs as a cost-cutting tool. We assess whether and to what extent the STC program is an effective alternative to layoffs by US firms.

Empirical support for STC as a prevention of job loss during economic downturns is mostly limited to aggregate cross-country studies (Abraham & Houseman, 1994; Boeri & Bruecker, 2011; Cahuc & Carcillo, 2011; Hijzen & Martin, 2013). From these studies, it can be hard to make conclusive statements about the success of the STC program in a given country without considering institutional differences and interactions with other labor market policies (Arico & Stein, 2012).[3] Using state-level manufacturing production data for the US, Abraham & Houseman (2014b) find that manufacturers in about half of the states that used STC during the 2008-2009 recession rely more on work hour adjustment than those in non-STC states.

Micro-level studies designed to test the findings of aggregate studies are scant and inconclusive. To our knowledge, there are only two US firm-level (evaluation) studies that estimate the STC program's impact on layoffs; the rest are concentrated on German and French firms. Kerachsky et al. (1986) estimate the extent to which the US STC program protected jobs in the 1982-1983 recession. They use UI administrative and employer survey data on firms in California, Arizona, and Oregon (the first three states to implement STC programs) and adjust for observable covariates via OLS to show that STC reduces the percent of time spent on regular UI by about 12%.[4] Needels et al. (1997) find the opposite results when they use administrative data for California, Kansas, Florida, New York and Washington and a matching technique (as well as OLS) to compare firms that use STC following the 1990s recession

[1] The pro-rated benefits paid are the share of Unemployment Insurance benefits a worker receives if laid off. The share is based on the fraction of work hours lost.

[2] STC benefits to the firm also include the savings from the wage, rehiring and retraining costs avoided, the flexibility gained in labor input adjustments, and the avoided adverse morale and productivity problems associated with being laid off. However, it costs to use sub-optimal amounts of labor input given the lower output demand and, as required by some state programs, to maintain fringe benefits during the STC plan.

[3] Arico & Stein (2012) argue that the more favorable institutional features of Germany's labor market contributed to better employment outcomes than Italy during the recent crisis, despite similar well-established STC policies. The institutional features of Germany's labor market include strong cooperation between employer and union, an efficient income support system and the interaction with other job retention policies.

[4] However, when non-STC firms with no propensity to use STC are removed from the sample (10% of sampled firms), the estimated effect falls and become insignificant. Their employer survey was used to identify the non-STC employers that consciously rejected the use of STC as having no propensity to use STC.

to non-STC firms.[5] Even firm-level studies in Germany and France provide limited guidance regarding what results to expect in the context of the US. Like Needels et al. (1997), Calavrezo et al. (2009, 2010) find that STC increases the incidence or extent of layoffs in France, even while using more rigorous IV/inverse Mills ratio techniques (Calavrezo et al., 2009) and propensity score matching (Calavrezo et al., 2010).[6] Whereas Boeri & Bruecker (2011) employ an IV method to show that a greater share of STC workers has a positive impact on employment growth by German plants in 2008-2009, Bellman et al. (2012) and Kruppe & Scholz (2014) find no significant effect using the same data, albeit using different methods (Bellman et al.: IV difference-in-difference and Kruppe & Scholz: propensity-score matching).

The contradictory evidence from micro-level studies reflects the complex nature of the relationship between STC use and layoffs that is perhaps driven by selectivity. There are two key reasons why firms that select into STC may differ significantly from those that do not. First, firms using STC are prone to excessive layoffs in times of economic hardship, a positive selection bias since these firms are more likely to use the program. But second, a negative selection bias may occur if firms that choose to use STC prefer hours reductions for retaining valuable workers (rather than layoffs) because these firms actually have the best prospects in response to a positive demand shock. These selectivity issues have made it difficult for existing studies to ascertain the impact of STC.

Our contribution is two-fold. First, we tackle both selection problems by econometrically classifying firms based on their workforce dynamics. To do so, we employ a finite mixture model (FMM) to identify latent groups of firms with statistically similar histories. We define relatively cyclically sensitive firms as ones having a history of employment fluctuations and a reliance on layoffs or work hour reductions, perhaps because they have a lower capitalized value to sustain losses or lower adjustment costs.[7] Also, to further guard against negative selection bias, we control for employee skill as a simulated unmeasured confounder à la Ichino et al. (2008).[8]

Second, given that no studies, to our knowledge, examine how STC's impact varies by firm characteristics, we show that the program may affect firms differently depending on their industry, labor costs, degree of workforce stability, and whether they are subsidized by the UI tax system. Thus, we identify heterogeneous layoff responses to a specific countercyclical benefit program, and thus contribute to the literature on labor hoarding in response to business cycle shocks. Accounting for firm heterogeneity is also important from a policy perspective because determining the relationship between STC effects and firm characteristics pinpoints the type of firms most likely to benefit. Knowing which firms benefit, and which

[5] Comparison non-STC firms were selected based on firm size, UI tax rate, and industry.

[6] Calavrezo et al. (2009) and other IV studies employ experience with STC (i.e. lagged STC take-up rate) as an instrument. Such estimates may be biased if the firms with past STC experience have a history of economic instability, or it could be that their early adoption indicates better management practices (or administrative capacity) that affect their resilience to demand shocks.

[7] Technical details are provided later.

[8] We adopt these approaches because there are no obvious valid instruments triggering STC use and there are inadequate data for fixed-effects estimation. Our approach enables us to estimate heterogeneous effects of STC based on latent classes of workforce dynamics.

do not, sheds light on why many firms do not participate. But also, identifying the characteristics that make STC more effective can enable policymakers to target firms at which the program will have the greatest impact.

We seek to answer three questions. Does STC deter layoffs? If so, by how much? And third, does STC work for all firms? We semi-parametrically estimate potentially heterogeneous effects of STC using UI administrative data on 2420 firms in five US states (California, Florida, Kansas, New York, and Washington) over the 1991-1993 period.[9] The FMM identifies latent groupings of stable and unstable firms based on cyclical sensitivity implicit in the quarterly 1991-1992 data on layoffs, work hour reductions, and employment fluctuations. Given this grouping, we reweight the 1993 subsample to account for non-random firm drop-outs and for firm selection into STC. These reweighted data are used to estimate the effect of STC on layoff rates.[10] This weighting scheme better allows us to compare the mean layoff rate of STC firms to their mean layoff rate had they not used STC. Such a comparison is then made based on firm characteristics. We find that the program is not effective for the typical STC firm, but that it very effectively reduces layoff rates for unstable STC firms by about 15%. Even greater reductions in layoff rates can be achieved if firms are exempt of tax charges for STC benefits when the program is targeted to unstable firms with significant labor costs.

The remainder of the paper is structured as follows. Section 2 reviews US participation in the STC program. Section 3 makes predictions about the effect of STC and how it may vary by firm characteristics. Section 4 describes the data. Section 5 outlines our three-step empirical strategy. Section 6 reports our estimation results, which includes checks for potential violations of the conditional independence identifying assumption. The final section summarizes and makes some concluding remarks regarding policy implications.

2 STC program participation in US

California was the first state to implement an STC program in 1978, following the mass public sector layoffs resulting from proposition 13 limiting state spending (Kerachsky et al., 1986). The onset of the 1982-1983 recession further motivated compensated work-sharing, which led to an extensive adoption of similar programs by an additional 18 states until 1992. Despite Congress enacting the first permanent STC legislation in that year, program implementations were dormant until 2009 when renewed interest in STC arose. This resurgence culminated in the development of a new federal law, passed in 2012, which further supported state adoption of STC programs. Currently, a slight majority of states amended their UI laws to allow increased program participation. They vary greatly in take-up rates and program-specific rules, but despite the growth in the number of STC states, program use has generally remained low. In 1991, STC benefits were less than 1% of regular UI benefits paid out and

[9] This US firm-level UI administrative dataset is the only one available for public-use. It contains the UI and STC records for 5 states (for reasons given in section 4) during one of the longest period of jobless recovery.

[10] Like other studies, we also employ a propensity-score matching method as a robustness check on the findings from the propensity-weighting method.

were still about the same in 2008 (Abraham & Houseman, 2014b).[11] Firms in STC states also made limited use of it. In 1994, based on 17 states, firm participation in STC averaged less than 1% of all UI participating firms (Needels et al., 1997).

It is not fully known what factors account for the low take-up of STC programs by US states and the subsequent low program participation by firms, though some contributing factors are proffered by Needels et al. (1997), Abraham & Houseman (2014a) and Balducchi et al. (2015). The low STC adoption by states may reflect resistance from stakeholders (state UI agency, unions etc.), a lack of knowledge or understanding about STC due to limited state promotions, the potential threat to the UI trust fund, concerns related to program administrative costs, and also whether STC is actually needed (e.g. if most firms in a state are small or non-manufacturing firms). States with less liberal political ideologies appear less likely to implement STC (Vroman, 2013). Employers themselves may be attracted to the program for different reasons. Kerachsky et al.'s (1986) and Balducchi et al. (2015) identify industry, financial health and human capital factors (wage and tenure) as factors associated with employers' STC use. Maintaining full fringe benefit and UI tax implications can also be relevant to employers' decisions to use STC; but Kerachsky et al. (1986) find little or no support for them. All these factors may have led to differential STC take-up by US firms.

3 Predicting layoff effects of STC

It is hard to predict whether using STC is an effective alternative to layoffs. The existing empirical work reveal three possible effects. First, STC can preclude layoffs by making it more cost-effective for firms to retain workers for when output demand picks up and full labor input is required. It is cost-effective in the sense that it can save employers in wage costs and preclude rehiring costs and skill losses. Second, STC may have no effect on layoffs if the firm that uses STC would have retained workers anyway in the absence of the program. Third, STC may promote layoffs, as demonstrated in the studies on French firms. One interpretation is that the recourse to STC is "a way for establishments to calm the social tensions before a planned redundancy scheme" (Calavrezo et al., 2009, p. 13). Another interpretation is that STC is positively related to layoffs because the program is typically aimed at firms in structural decline —a positive selection bias.

To further complicate matters, it is also possible that some firms benefit while others do not. How firm-specific characteristics affect STC's impact on layoffs is an issue *not* currently addressed in the empirical literature. For instance, cyclically sensitive less stable firms, with revenues that are so sensitive to demand conditions that they have unstable employment and habitually rely on laying off workers or reducing work hours when demand is low, may benefit more than the typical firm. For these firms, we expect the impact of STC to depend on the extent of firms' workforce stability because less stable firms are more exposed to excessive layoffs.

[11] The STC usage rate was higher than 1% during the 2009-2010 recessionary years, but still was quite low by international standards.

Similarly, a firm's degree of experience rating can affect the program's effectiveness. Firms that incur UI tax charges that do not cover the benefits paid out to employees laid off or to those with shorter work schedules are said to be imperfectly experience rated. This is especially true for those firms at their state's statutory minimum or maximum tax rate.[12] These firms incur little or no marginal cost, and thus are effectively subsidized, since their tax rates tend not to increase with further reliance on compensated unemployment (UI and STC) benefits (Abraham & Houseman, 2014b). Thus, conditioning on firms' history of workforce dynamics, we expect that such subsidized STC firms would be more induced to make work-hour adjustments under STC instead of resorting to layoffs.[13] In other words, if the extent to which firms share in the cost of STC provision reflects the degree of generosity of the program (Hijzen & Venn, 2011), then a more generous STC program should be more effective at reducing layoffs (Van Audenrode, 1994).

Likewise, firms with high labor costs may also react quite differently to STC use than firms with low labor costs. If indeed high-wage paying firms attract more productive workers (Abowd et al., 1999), then they are likely to suffer greater human capital losses from layoffs, and hence higher rehiring and retraining costs. Dube et al. (2010) find evidence of a positive relationship between such replacement costs and wage. Therefore, consistent with Van Audenrode's (1994) theoretical findings, we can expect higher replacement costs faced by high-wage paying firms to foster greater substitution of employment reduction in favor of shorter work schedules.

Finally, the effect of STC may vary by the industry in which firms operate. Manufacturing firms are more likely to use STC than other firms (MaCurdy et al., 2004). Since manufacturing firms (electronics, industrial machinery etc.) tend to use specialized labor skills that are mainly acquired through apprenticeship and on-the-job-training, the effect of STC may be stronger for such firms to avoid the costs of retraining and rehiring when business improves. However, since manufacturing firms also tend to be more capital intensive (Helper et al., 2012), they might find it relatively more expensive to adopt shorter work schedules. For instance, high start-up and shutdown costs of capital equipment for some manufacturing operations may discourage frequent plant shutdowns associated with shorter work shifts (Lilien & Hall, 1986).[14] By this argument, STC's impact may be moderated for manufacturing firms.

[12] In our sample, virtually all subsidized firms are at the maximum tax rate. Less than 1% of firms are at the minimum tax rate. We also considered states with special provisions that affect the maximum UI tax rate. In the 1990's, these entail only two states, Florida and Missouri, that apply a super maximum tax rate to STC employers with tax liabilities exceeding the state's maximum UI tax rate (Needels et al., 1997). So, in those states, we treat STC firms as subsidized if they are at the super maximum rate, otherwise not.

[13] Whereas typically being at the maximum UI tax rate may indicate a distressed firm's past economic difficulties, this is not the case here because we condition on workforce stability in our analyses.

[14] It is worth noting that, according to Mattey & Strongin (1997), just about 50% of manufacturing firms operate 24 hours per day for at least 5 days per week, based on the Census Survey of Plant Capacity microdata (1979-1988).

4 Data

We employ Needels et al.'s (1997) public-use, US firm-level, UI administrative data.[15] It records 1991-1993 data for a sample of 3415 firms in California, Florida, Kansas, New York and Washington. Of the 17 states with active STC programs at the time, these 5 states were reported to have substantial employer participation, adequate and accessible records of key variables, and were diverse in terms of geography, economy, demography and program-specific rules (see table 1). Whereas the sample contains all firms in Florida, Kansas and Washington that filed an STC plan in 1992, it only includes a random sample of STC firms from California and New York.[16] The sample also includes comparison firms with no STC plan over the same time period. The corresponding non-STC firms are similar to the STC firms based on Standard Industrial Classification (SIC) code, UI tax rate, and employment size.[17] These data still have relevance for current analysis, given that the basic structure of the STC program and its adoption rate have remained low.

Our layoff measure is the number of new UI claimants to the firm.[18] We estimate the effect of STC use on layoff rates in 1993.[19] We employ firms' 1991-1992 histories to implement the FMM (described in the next section) for uncovering latent classes of firms that are statistically similar in workforce cyclicality. The FMM uses quarterly data on total compensated unemployment benefit (as a fraction of full-time equivalent payroll) and employee count (as a fraction of the maximum count over 1991-1992).[20] We exclude 915 firms with missing values in the variables employed in the FMM. In any case, the distribution of the layoff rate of firms operating in 1993 and the proportion that use STC (35%) remains virtually unchanged. In the remaining sample, about 3% of firms closed business in 1993. Such firm drop-outs may create a non-random selection of firms if they tend to be the economically weak ones. Our empirical strategy adjusts for firm drop-outs. The estimation sample has 2420 firms.

[15] Data downloaded from the Employment Research Data Center of the W.E. Upjohn Institute for Employment Research. Data on 47 firms were not published to restrict their identity. In addition, the data contain only the one-digit Standard Industrial Classification code.

[16] Program participation in California and New York far exceeded those in other states.

[17] Needels et al. (1997) choose comparison firms (those not filing an STC plan) based on three-digit SIC, quintiles of the 1992 UI tax rate, and quintiles of employment size. Firms that file STC plans are not necessarily the same ones that actually end up using STC in a given period. Our analysis is based on use of STC rather than simply filing for a plan. So, we control for industry (one-digit SIC), and for the levels (rather than quintiles) of employment and UI tax rate via a propensity score weighting procedure.

[18] Since UI claims are usually filed after job loss, it should trend closely with actual layoffs and discharges series. Note, however, that those employees who are eligible for UI but do not claim benefits are not accounted for by this layoff measure. Also, some UI claims drawn on a firm may not reflect layoffs by that firm if, for instance, the laid off worker had more than one base-period employer. However, we suspect that, in large part, these issues are inconsequential.

[19] Layoff rate is computed as the number of new UI claimants in 1993 as a proportion of employment size in 1992. We apply Vandervieren & Hubert (2004) method to identify outliers from this layoff rate variable. The method is applicable to variables that have naturally skewed distributions. Thirteen layoff rate observations are discarded as outliers.

[20] Full-time equivalent payroll is the total wage an employer would have paid out if no workers were laid off or their hours reduced. It is computed as the total wage plus 2 times the sum of regular UI benefits and STC benefits, assuming a replacement rate of 50%. In regard to employee count, by dividing it by the maximum count over 1991-1992, we constrain it between 0 and 1 to allow for comparison across firms.

The first row of table 2 reports an average layoff rate in 1993 of 12.5%, with STC firms' layoff rate (13.8%) being higher than that of non-STC firms (11.8%). Based on the next two variables in table 2, it appears that the typical STC firm (unlike the non-STC firm) suffered a decline in workforce over the 1991-1992 period from 79 to 75 workers. This pattern is reflected in a higher rate of increase (from 2% to 3%) in unemployment benefits charged to STC firms (as a percent of payroll), relative to non-STC firms (from 1.5% to 2.0%). Although these descriptives (on annual data) indicate STC firms are larger but more cyclically sensitive (being more prone layoff workers), we make a more rigorous assessment using the FMM at a later stage.

The remaining variables in table 2 may affect selection into STC. While STC firms tend to be bigger in terms of employee count than non-STC firms (over 70 vs. about 50 workers), the average (log) wage per employee is not significantly different. Regarding firms' tax contribution, we normalize UI tax rates (at the start of 1993) to lie between -1 and 1, for comparability across states, since each US state sets different statutory minimum and maximum tax rates.[21] A value of -1 or 1 means that a firm is paying the minimum or maximum tax rate, respectively. Thus, UI benefits charged to that firm do not affect its tax payments and the firm is said to receive a pure subsidy (i.e. imperfectly experience rated). Table 2 shows that STC firms incur a higher normalized tax rate (0.54 vs. 0.38). They are also more likely to receive a pure subsidy (31.5% vs. 20.9%). The table also shows that the total tax contribution of firms to the UI trust fund over 1991-1992, on average, do not cover the benefits paid out. That is, the net balance (as a percent of taxable wage) is -5.1%, and it gets more negative for STC firms (-8.0%). This means tax rates do not rise sufficiently to cover the full UI benefits, and more so for STC firms.

The sample covers the industrial sector and US states where STC use is most common. Manufacturing firms are known to be popular users of STC (MaCurdy et al., 2004). So, it is encouraging that they are well-represented in the overall sample (45.1%) and also more representative of the sample STC firms (50.2%) than the non-STC ones (42.4%). As expected, California and New York comprise the majority of our sample (64.3%), and both represent the majority of STC firms in the early 1990's.[22]

5 Empirical strategy

5.1 Parameter of interest

The effect of firms *using* STC on their layoff rates is measured by comparing the layoff rates of these STC firms to their layoff rates had they not used STC. Formally, let S be an

[21] Let t_{is} represents the UI tax rate (at the start of 1993) for firm i in state s. Then, we normalize the UI tax rate as follows for firm i in state s: $[2t_{is} - \max(t_{is}) - \min(t_{is})]/[\max(t_{is}) - \min(t_{is})]$. Our basic results are not sensitive to this normalization; they are qualitatively unchanged when the untransformed tax rate is used.

[22] We account for state fixed effects to capture differences in economic conditions, UI laws and labor market conditions.

indicator variable, which takes on 1 if a firm uses STC and 0 if it does not. If the firm uses STC ($S = 1$), its layoff rate is ℓ_1, and it is ℓ_0 if that same firm does not use STC ($S = 0$).[23] We estimate the average effect of firms' STC use on their layoff rates, which varies based on firm-specific attributes. Our parameter of interest is

$$\beta(\boldsymbol{z}) = E(\ell_1|S = 1, \boldsymbol{Z} = \boldsymbol{z})/E(\ell_0|S = 1, \boldsymbol{Z} = \boldsymbol{z}) = \beta_1(\boldsymbol{z})/\beta_0(\boldsymbol{z}) \tag{1}$$

where $\boldsymbol{Z}$ is a vector of firm characteristics that impact the effectiveness of the STC program (e.g. labor costs); $\beta_1(\boldsymbol{z})$ is the mean layoff rate among STC firms with particular characteristics $\boldsymbol{z}$; and $\beta_0(\boldsymbol{z})$ is their counterfactual mean layoff rate had the firms not used STC. We interpret the quantity $[\beta(\boldsymbol{z}) - 1]$ as the relative change in the layoff rate of STC firms with particular characteristics $\boldsymbol{z}$.[24] Let β be the relative STC effect that is unconditional on $\boldsymbol{Z}$. We follow a three-step procedure to estimate the parameter $\beta(\boldsymbol{z})$ in equation 1:

a. Distinguish firms based on their history of workforce dynamics using the FMM.

b. Estimate the constant relative STC effect β, using two probability weights to:

   (i) adjust for firm drop-outs by up-weighting firms in the estimation sample that are similar in workforce dynamics; and

   (ii) adjust for selection into STC by up-weighting non-STC firms closest to the STC ones (in terms of observables) among firms with similar workforce dynamics.

c. Non-parametrically estimate β for a given firm with $\boldsymbol{Z} = \boldsymbol{z}$, that is $\beta(\boldsymbol{z})$, where $\boldsymbol{Z}$ also includes an indicator for firms' degree of workforce stability.

5.2 Identifying firms differing in workforce dynamics

In this study, a cyclically unstable firm is defined as one which has a history of high reliance on work hour reductions, layoffs, and unstable employment during or following an economic downturn. Such unstable firms often react by laying off employees or reducing unit labor costs to raise liquidity in order to pay current debts (John et al., 1992; DeAngelo & DeAngelo, 1991). Based on firms' histories of compensated unemployment charges and employment adjustments, we employ FMM to create different groups of firms that vary in workforce stability. The FMM generally identifies latent groups of firms, given that *a priori* firms differ by their class of cyclical workforce dynamics, which we denote as C.

To describe the FMM procedure, consider the multivariate vector $\boldsymbol{y}_{i,1:T} = (\boldsymbol{y}'_{i,1} \ldots \boldsymbol{y}'_{i,T})'$, which in our data represent the history of total compensated unemployment charges and

[23] Like Kerachsky et al. (1986) and Needels et al. (1997), we focus on participation of firms in the STC program (extensive margin) rather than firms' STC usage rate (intensive margin) adopted by non-US studies. We believe, in light of the low prevalence of STC firms in the US, the participation decision is the more important margin on which to assess the success of the STC program in reducing firms' layoff rate.

[24] We can also interpret $\beta(\boldsymbol{z})$ as a layoff conversion rate —the degree to which an STC firm's full-time equivalent workers substitute for the layoffs it would have otherwise experienced. $\beta(\boldsymbol{z}) = 0$ implies a perfect substitution so that each full-time equivalent worker on STC replaces a laid off worker in firms with attributes $\boldsymbol{z}$.

employment adjustments over T quarterly time periods for firm i. We might expect for instance that $\boldsymbol{y}_{i,1:T}$ for relatively cyclically unstable firms is distributed differently from relatively stable firms. If so, then "the observed data [on $\boldsymbol{y}_{i,1:T}$] are drawn from a mix of distinct underlying populations" (Greene, 2012, p. 630). One can define the probability (π_g) of a firm being drawn from one population group g or the other and write out the density $f(\cdot)$ for $\boldsymbol{y}_{i,1:T}$ as a weighted sum as follows:

$$f(\boldsymbol{y}_{i,1:T};\ \boldsymbol{\theta}_{1:G,1:T},\ \pi_{1:G}) = \sum_{c=1}^{G} \pi_c \cdot \boldsymbol{\phi}(\boldsymbol{y}_{i,1:T}; \boldsymbol{\theta}_{c,1:T}) \tag{2}$$

where G represents the number of groups, 1:G denotes parameters for groups 1 to G; and $\boldsymbol{\phi}(\boldsymbol{y}_{i,1:T}; \boldsymbol{\theta}_{c,1:T})$ represents a conditional (on group c) multivariate normal density of $\boldsymbol{y}_{i,1:T}$ for firm i with group-specific parameters that vary across time contained in $\boldsymbol{\theta}_{c,1:T}$. The parameter $\boldsymbol{\theta}_{c,1:T}$ (especially the mean) is useful for describing the differences in firm groupings in terms of the extent of reliance on layoffs and work hour reduction and employment adjustments over time. The number of groups (G) and the parameters ($\boldsymbol{\theta}_{1:G,1:T},\ \pi_{1:G}$) are determined entirely from the data by maximizing the log-likelihood function of equation 2.[25] In so doing, we avoid biases that may arise when firms are grouped by imposing arbitrary cutoff levels for multiple variables in $\boldsymbol{y}_{i,1:T}$. The population group from which an observed firm is drawn can also be determined by using equation 2 and Bayes' theorem.[26] The idea is to assign a firm with a given history $\boldsymbol{y}_{i,1:T}$ to the group c if $\boldsymbol{y}_{i,1:T}$ most likely derives from a density $\boldsymbol{\phi}$ with parameter $\boldsymbol{\theta}_{c,1:T}$. The result is an estimated ordered categorical variable $\hat{C}$ that classifies firms with similar workforce histories. We then account for $\hat{C}$ in two ways. First, it is used to achieve greater similarity between STC and non-STC firms via probability weights for dealing with selectivity issues (step b). Second, it is included in $\boldsymbol{Z}$ to estimate STC effects that also vary by the extent of workforce stability (step c).

5.3 Estimate constant STC effect

To estimate β, we address two selectivity issues: sample attrition (drop-outs) and selection into STC. First, we consider firm drop-outs. If in the data, some cease operating during or following a downturn, then such firms are more likely to be economically weak and the observed data is likely to contain a non-random selection of firms. To make our sample representative of the contribution of such weak firms that later drop-out, we up-weight observed firms that are similarly unstable. To do this, we estimate the probability of not dropping out, given firms' workforce histories $Pr(A = 0|\hat{C})$, where A indicates whether a

[25] The log-likelihood function is maximized (using an E-M algorithm) first for a single group of firms and then for 2, 3, 4 and 5 groups of firms. Fraley & Raftery (2002) suggest that the number of groups be small to avoid groups containing a few observations that may cause the E-M algorithm to fail or give erroneous results. They recommend the optimal value of G that minimizes the Bayesian Information Criterion.

[26] Formally, a firm i with a given history $y_{i,1:T}$ belongs to group c if it maximizes the conditional probability of belonging to that group, $\pi_{c|y_{i,1:T}} = \pi_c \cdot \boldsymbol{\phi}(\boldsymbol{y}_{i,1:T}; \boldsymbol{\theta}_{c,1:T}) / f(\boldsymbol{y}_{i,1:T};\ \boldsymbol{\theta}_{1:G,1:T},\ \pi_{1:G})$. For example, if there are two groups (unstable and stable firms), a firm is classified as unstable if the conditional probability of being unstable is larger than 0.5.

firm later drops out.[27] We then define a variable $w = 1/Pr(A = 0|\hat{C})$, which assigns a weight to observed firms that corrects the number of firms represented in each category of workforce stability ($\hat{C}$). When w is applied, less more cyclically sensitive weaker firms are given more weight.

Second, we consider firm selection into STC. The problem here is that one cannot observe the mean layoff rate for STC firms had they not used STC, that is, $E(\ell_0|S = 1)$. If firms that use STC are systematically different from firms that do not, then one cannot simply set the observed mean layoff rate for non-STC firms $E(\ell_0|S = 0)$ equal to $E(\ell_0|S = 1)$. Let $\boldsymbol{X}$ be observed firm characteristics that affect the decision to use STC. Our key identifying assumption is that the probability of selection into STC depends on $\boldsymbol{X}$ within each estimated category ($\hat{c}$) of employment history, that is, $p_{\hat{c}} = Pr(S = 1|\boldsymbol{X}, \hat{C} = \hat{c})$. As such, conditioning on $p_{\hat{c}}$ is enough to ensure the layoff rate in the absence of using STC (ℓ_0) is not different for STC and non-STC firms. In other words, conditional independence of ℓ_0 and S is assumed to be achieved within each latent class of employment history.[28]

In estimating $E(\ell_0|S = 1)$, we weight non-STC firms' layoff rates by $w_{\hat{c}} = p_{\hat{c}}/(1 - p_{\hat{c}})$, where $p_{\hat{c}} < 1$. More weight is assigned to non-STC firms with relatively high odds $w_{\hat{c}}$ of using STC based on their characteristics ($\hat{C}$, $\boldsymbol{X}'$) but still choosing not to use the STC program. We consider such firms similar to STC firms. We apply inverse probability weighting (IPW) to estimate the mean counterfactual outcome $E(\ell_0|S = 1)$ as $E(w_{\hat{c}}(1 - S)\ell))/E(S)$, where ℓ is the observed layoff rate (see Wooldridge, 2002, p. 615).[29] The mean layoff rate of STC firms $E(\ell_1|S = 1)$ is easily computed as $E(S\ell)/E(S)$. Let $\hat{w}_i$ and $\hat{w}_{i,\hat{c}_i}$ be the estimated attrition and selection weights respectively for firm i. Since $\beta = E(\ell_1|S = 1)/E(\ell_0|S = 1)$, using the sample counterpart of the expectation operator, we estimate the constant relative STC effect corrected for attrition and self-selection bias as follows:

$$\hat{\beta} = \frac{\sum_{i=1}^{n} \hat{w}_i S_i \ell_i}{\sum_{i=1}^{n} \hat{w}_i \hat{w}_{i,\hat{c}_i}(1 - S_i)\ell_i} \tag{3}$$

Basu et al. (2008) provide support for the consistency of the IPW for response variables that are non-negative and positively skewed (e.g. layoff rate).[30] The IPW estimator is also competitive with matching estimators when there are sufficient comparable treated and control units (Busso et al., 2014), as in our case. Nevertheless, we use matching (via a local linear ridge regression) to support the IPW since Frolich (2004) finds it achieves the lowest mean squared error of all considered estimators (including IPW).[31]

[27] We also include all our other observables and obtain very similar results.

[28] Section 6.3.2 provides indirect evidence supporting the robustness of our estimates to a potentially key unmeasured omitted variables namely employee skill.

[29] We also consider an estimator with normalized weights that sum to one and find a similar estimate of -0.095 at the 5% significant level (compared to the -0.107 reported in table 4, column 5).

[30] Basu et al. (2008) find that the IPW estimator is always consistent when the probability model of selection is over-specified with quadratic and interaction terms as well as the main effects of $\boldsymbol{X}$.

[31] In local linear ridge matching estimator, the counterfactual layoff rate of STC firms is estimated by a local linear ridge regression. Essentially, a ridge term (pre-chosen constant) is added to the denominator of an OLS estimator to avoid division by values close to zero. The estimator tends to improve in variance, although attenuated toward zero. Another disadvantage of this estimator is that a bandwidth parameter needs to be determined.

5.4 Estimate heterogeneous STC effects

In line with our expectations from section 3 that the effectiveness of STC depends on firm attributes ($\boldsymbol{Z}$), we now estimate β for a given firm with $\boldsymbol{Z} = \boldsymbol{z}$, that is, $\beta(\boldsymbol{z})$.[32] Rather than commit to a particular functional form, we non-parametrically derive firm-specific estimates corresponding to each observed combination of attributes in $\boldsymbol{Z}$ by modifying equation 3 as:

$$\hat{\beta}(\boldsymbol{z}) = \frac{\sum_{i=1}^{n} K_h(\boldsymbol{Z}_i - \boldsymbol{z})\hat{w}_i S_i \ell_i}{\sum_{i=1}^{n} K_h(\boldsymbol{Z}_i - \boldsymbol{z})\hat{w}_i \hat{w}_{i,\hat{c}_i}(1 - S_i)\ell_i} \tag{4}$$

where $K_h(\boldsymbol{Z}_i - \boldsymbol{z})$ is a kernel weight function that measures the distance between $\boldsymbol{Z}_i$ and $\boldsymbol{z}$, and then assigns a relatively high weight if firm i possesses attributes similar to the combination in $\boldsymbol{z}$.[33] The parameter h (the bandwidth) determines the set of firms with features considered close to $\boldsymbol{z}$.[34] We use Li & Racine's (2010, p. 1617) specification test to check the relevance of the $\boldsymbol{Z}$ variables as moderators of the effect of firms' STC use on the layoff rate.[35]

To assess the statistical significance of $\hat{\beta}(\boldsymbol{z})$, as well as the constant effect $\hat{\beta}$, we compute standard errors using pairs bootstrap samples. Since group membership based on workforce dynamics and the probability of sample attrition and selection into STC are estimated beforehand, the sampling error inherent in their estimation must be incorporated in the standard errors of $\hat{\beta}$ and $\hat{\beta}(\boldsymbol{z})$. As such, the entire three-step procedure, just outlined, is bootstrapped 500 times to compute standard errors.

6 Estimation results

At the outset, we identify the latent groups of firms that differ in employment histories. Conditional on these groups, we then compute two probability weights for sample attrition and selection into STC. These weights are used in estimating the effectiveness of the STC program in precluding firms' layoffs. We then check for violations of our identifying assumption.

[32] Under our identifying assumption, when $\boldsymbol{Z}$ is a subset of ($\hat{C}$, $\boldsymbol{X}'$), it can be shown using the tower property that $E(\ell_1|S = 1, \boldsymbol{Z}) = E(S\ell|\boldsymbol{Z})/E(S|\boldsymbol{Z})$ and $E(\ell_0|S = 1, \boldsymbol{Z}) = E(\hat{w}_{i,\hat{c}_i}(1 - S)\ell|\boldsymbol{Z})/E(S|\boldsymbol{Z})$.

[33] As in Li & Racine (2007), we used a generalized product kernel function $K_h(\boldsymbol{Z}_i - \boldsymbol{z})$, comprising of a mixture of second-order Epanechnikov (for continuous data) and Aitchison-Aitken (for binary data) kernels, to weight neighborhood observations such that weights increase with closer proximity to $\boldsymbol{z}$.

[34] The bandwidth h is chosen by cross-validation (CV). The sum of squared out-of-sample forecast error of STC firms' layoff rate is minimized: $h^{CV} = \arg\max_h \sum_{i:S_i=1}[\ell_i - \hat{\beta}_1^{-i}(\boldsymbol{z}_i)]^2$, where $\hat{\beta}_1^{-i}(\boldsymbol{z}_i)$ is the predicted mean layoff rate of STC firm i with attribute $\boldsymbol{z}$ after leaving it out of the sample.

[35] We use Li & Racine's (2010) test statistic to test the null hypothesis: $\beta_1(\boldsymbol{z}_i) = \beta_1$. Under the null, $\ell_i^* = \beta_1 x_i^* + \epsilon_i^*$, for $i : S_i = 1$, where $\ell_i^* = \sqrt{\hat{w}_i}\ell_i$, $x_i^* = \sqrt{\hat{w}_i}$ and $\epsilon_i^* = \sqrt{\hat{w}_i}\epsilon_i$ is an error term.

6.1 Latent firm groupings

Using quarterly 1991-1992 data on both the firms in the estimation sample and those that dropped out in 1993, we find the FMM results suggest the presence of two groups of firms with different workforce dynamics. This number of groups is optimal in the sense that it corresponds to the lowest Bayesian Information Criterion value. In other words, the gain in goodness-of-fit from segmenting the data into two groups of firms is 18%, after accounting for the loss in degrees of freedom from estimating the FMM parameters.

Figure 1 shows how the groups differ in terms of their histories of work hour reductions and layoffs and their instability in employment over the 1991-1992 period. The solid (dotted) line indicates the mean historical trajectory for firms in group 1 (group 2), as estimated from the FMM. Based on firm charges for compensated unemployment benefits (as a fraction of full-time equivalent payroll), figure 1a shows that firms in group 1 have a history of high reliance on work hour reductions and layoffs. Although for both groups unemployment worsened somewhat following the end of the 1990-1991 downturn, it is clear that firms in group 1 are more sensitive to demand fluctuations. We also use data on employee count as a proportion of the maximum count attained over the 1991-1992 period. A lower proportion means a greater deviation in employee count from the maximum level attained over the period. Figure 1b shows that firms in group 2 are quite stable as they generally hovered around a proportion of 0.85 employed. However, the firms in group 1 appear to suffer greater instability in their employment adjustments to demand fluctuations. Their proportions are well below 0.85 especially in the first quarter of 1992 when US employment reached its trough. We refer to firms in group 1 (group 2) as cyclically unstable (stable) firms, which consists of about 39% (61%) of the firms in the sample.

The grouping of firms by extent of workforce stability via the FMM is consistent with expected patterns.[36] First, STC firms are more likely to be cyclically unstable. The odds of a cyclically unstable firm using STC is nearly two times higher than that of a cyclically stable firm; hence, the importance of controlling for extent of workforce stability. Second, those firms that dropped out of the sample in 1993 are more likely to be unstable. The odds are about four times greater that a cyclically unstable firm will not remain in business than a cyclically stable firm. This finding suggests that there may be a non-random selection of firms in our estimation sample. As such, the contributions of unstable firms in the estimation sample are given a higher weight to address bias due to sample attrition.

6.2 Firm selection into STC: overlap and balance

To estimate the mean layoff rate for STC firms had they not used STC, we give higher weights to non-STC firms that have high odds of selecting into STC. As such, the prob-

[36] We also relate our grouping of firms to other firm characteristics available from a subsample of 500 firms (surveyed by Needels et al. (1997) that used STC in 1992. As expected, unstable firms are more likely to have characteristics indicating financial constraints, such as no offer of health benefits or retirement plan and experiencing a financial loss. Characteristics we expect to be unrelated to a firm's workforce stability, such as the percentage of employees of a given gender or race, are indeed unrelated.

ability of selecting into STC is estimated as a function of the covariates listed in table 3, their quadratics, and two-way interactions of the workforce stability indicator with all other covariates. In line with the suggestions of Brookhart et al. (2006), all covariates are either related to the layoff rate or related to both the layoff rate and whether firms use STC. The use of the quadratic and interaction terms is consistent with the approach of Dehejia & Wahba (1999), Morgan & Todd (2008) and Basu et al. (2008).[37]

We include in further analysis only STC and non-STC firms that have comparable values of the estimated probability of selection into STC (the overlap or common support region). This approach ensures the availability of both STC and non-STC firms that have similar propensity to use STC. As suggested by Imbens (2004), we detect the extent of overlap by plotting separately for STC and non-STC firms the density of the estimated probabilities of selecting into STC. From figure 2, the two densities overlap quite well. In only about 3% of the cases, there are no estimated probabilities in common to STC and non-STC firms in the tails of the distributions. Thus, the estimation sample comprises the common support region (2353 observations).

We verify that the probability weights for selection into STC increase the similarity of STC and non-STC firms by performing a balancing check. As is typical in the literature (see for e.g. Morgan & Todd (2008)), we use the absolute standardized difference (ASDIFF) to compare the mean of a given covariate for STC firms to its weighted mean for non-STC firms. Table 3 provides the ASDIFF values and the means of the covariates separately for STC and non-STC firms, when non-STC firms are weighted (in the common support region) and also when they are not weighted (without the common support restriction). It is clear that the estimated probability weights substantially increase the comparability of STC and non-STC firms.[38] The average ASDIFF value dropped by over 90% from 0.151. In all cases, the differences in the means of the covariates are not significant after applying the weights.

6.3 Is the STC program effective?

6.3.1 Constant effect

Table 4 reports the estimates of the constant effect (β) of firms using STC on their layoff rates in 1993. Column 1 provides a simple difference-in-means estimate that compares the mean layoff rate of STC firms to that of non-STC firms. Using STC significantly (at the 1% level) increases layoff rates by 16.5%. However, when firms' degree of workforce stability is controlled for in column 2, the effect falls by about 12 percentage points and is not significantly different from zero. Further controlling for other covariates (including quadratics

[37] We also considered cubic variables and other two-way interactions, and estimated the probability of STC use by a local linear regression (instead of a probit regression), but covariate balance deteriorated. This is also true if we directly include the quarterly history of total compensated unemployment charges and employment adjustments in the propensity score.

[38] Since the estimated workforce stability indicator is a latent variable that groups firms that have a similar history of workforce adjustment, it may also be useful in controlling for unobserved time-varying and time-invariant factors that are correlated with it.

and two-way interactions of the workforce stability indicator with all covariates), column 3 shows STC use reduces layoff rates by on average 8.2%, albeit statistically insignificant.

It is quite possible, however, that there are comparability issues from using a standard multiple linear regression. Such a regression is based on the equal weighting of observations; no common support region (allowing for extrapolation and reduced precision); and the functional form assumption of a linear effect for all covariates. We therefore use two semi-parametric methods: the matching estimator supported by Frolich (2004) and the IPW estimator (equation 3). These methods give more weight to observations that are similar, use a common support region, and make no functional form assumptions aside from estimating the probability of selection using a probit model. Based on the matching estimator, we find that on average the layoff rates of STC firms are significantly (at the 10% level) lower by 9.4% (column 4 of table 4) than if they had not used STC. In comparison, the IPW estimate is -10.7% and statistically significant at the 5% level (column 5 of table 4). As expected, these semi-parametric estimators also achieve lower standard errors than OLS. Frolich (2004) prefers the matching estimator because of the greater precision it achieves. Indeed, the standard error of the estimate based on matching (0.049) is not different from that of the IPW estimate (0.050). Given the same precision of the IPW and matching estimators in our application, and given that the former performs well when overlap is good (Busso et al., 2014), we rely on the IPW estimator for further analysis.

6.3.2 A sensitivity check

So far, we have assumed the covariates (including the workforce stability indicator) are sufficient to identify comparable non-STC firms. Here we check the sensitivity of our estimates to a possible omitted variable namely worker skills, which could drive our estimates toward zero. Suppose firms' stock of human capital (e.g. tenure, productivity), which we will simply call 'skill', affects both the selection into STC and the layoff rate, and hence threaten the validity of our IPW estimate in table 4.[39] Suppose high-skilled firms are more likely to use STC (MaCurdy et al., 2004) to avoid skill loss and, in the absence of the STC program, they have lower layoff rates.[40] Following Ichino et al. (2008), we check our estimate's sensitivity to such an omitted variable by simulating it and then using it in equation 3.[41] That is, we

[39] For simplicity, we use the constant IPW estimate, rather than the heterogeneous IPW estimates, in the implementation of the simulation exercise we perform next.

[40] A countervailing possibility is that high-skilled workers may not favor STC because the pay reductions from participating in the program can be avoided by finding alternative full-time employment (Gray, 1998).

[41] Denote the unobserved confounder 'skill' as a binary variable U. Let the probability that $U = 1$ by STC status and layoff rate be denoted as $p_{ij} = Pr(U = 1|S = i, Y = j)$, with $i, j = 0, 1$ and $Y = 1$ if layoff rate is higher than its mean and 0 otherwise. Consequently, the fraction of firms with $U = 1$ by STC status is $p_{i.} = \sum_{j=0}^{1} p_{ij} \cdot Pr(Y = j|S = i)$. Note that the prevalence of firms in our sample with average wage per worker higher than the mean is about 40%. So, we assume, as in Ichino et al. (2008), that $Pr(U = 1) = 0.4$ (the prevalence of high-skilled firms) and $p_{11} - p_{10} = 0$ (the layoff effect of U when STC is used). Then, the layoff effect of U in the absence of the program ($d = p_{01} - p_{00}$) and the effect of U on selection into STC ($s = p_{1.} - p_{0.}$) uniquely determine the parameters p_{ij} for imputing the values of U. A hundred simulations of U are performed for a given set of parameters p_{ij}, then $\hat{\beta}$ is computed for each simulation, and the mean of the estimates reported.

construct the distribution of skill so that it has a positive effect (of size s) on selection into STC but a negative effect (of size d) on the layoff rate in the program's absence. We then determine the values of d and s necessary to drive the IPW estimate close to zero. If those d and s values are implausibly large, this analysis would support the validity of the IPW estimate.

In table 5, we show how the IPW estimate varies in response to different values of d and s. When $d = -0.20$ and $s = 0.20$, the IPW estimate becomes -2.2%. To put this finding into perspective, suppose we calibrate the distribution of skill to mimic that of the average wage per worker, since high-wage firms attract more productive workers (Abowd et al., 1999).[42] In that case, $d = -0.09$, $s = 0.01$, and the IPW estimate is -10.4% (not shown in table), which suggests a negligible effect on the baseline IPW estimate. It follows that the selection and layoff effects of skill would need to be substantially larger (in absolute value) than $d = -0.09$ and $s = 0.01$ to drive the IPW estimate to zero. Even if we increase s to 0.10, the estimate still remains economically significant (about -8.3%). These findings give credence to the robustness of our IPW estimator.

6.3.3 Heterogeneous effects

In section 3, we predicted the effect of STC may vary with specific firm attributes, that is $\beta(\mathbf{z})$. The firm attributes we consider are the degree of workforce stability, whether firms operate in the manufacturing industry, extent to which firms are subsidized by the UI tax system, and wage level. Yet the methods so far presuppose the effect is the same irrespective of these features. Indeed, the model specification test of Li & Racine (2010) rejects a constant effect in favor of heterogeneous effects based on a zero bootstrapped p-value. This test result supports the joint relevance of the four firm attributes as moderators of the effect of STC.[43] As such, further results are based on the estimation of equation 4, which provides firm-specific parameter estimates that correspond to each firm's combination on the four attributes of interest. We present the distribution of these estimates graphically in figure 3 and compress the results by reporting the estimates at the mean and the quartiles (P_{25}, P_{50}, and P_{75}) in panel 1, column 1 of table 6. At a later stage, we show how these results differ by specific features of firms in order to investigate heterogeneous layoff effects.

In support of the model specification test, figure 3 shows a double-peaked distribution of STC effects that clearly varies based on the features of firms. The estimates with the highest frequency occurs at about -8%, while those with the second highest frequency occurs at about -25%. The middle 50% of the estimates in the figure ranges from about -14.4% to 4.7% (statistically insignificant), with an insignificant mean estimate of -5.5% (see panel 1,

[42] For the unobserved confounder 'skill' (denoted as the binary variable U) to mimic the distribution of average wage per worker, the latter must be transformed to a binary variable. This is done by assigning a value of 1 to firms with average wage per worker higher than its mean, and a value of 0 otherwise.

[43] Moreover, the relatively small bandwidths associated with the $\mathbf{Z}$ variables (logarithm of average wage per worker, a manufacturing dummy, a workforce stability dummy and the tax rate (normalized)) of 0.424, 0.500, 0.057 and 0.198, respectively, suggest that these variables interact non-linearly with the STC effect. Hall et al. (2007) show that a bandwidth less than two times the standard deviation for a continuous variable or less than unity for a discrete variable is considered small.

column 1 of table 6). Allowing for heterogeneity, we now conclude that the typical STC firm may not benefit from STC use; but, depending on some specific features of the STC firm, its layoff rate can be reduced by over 14%. In other words, ignoring heterogeneity (as is the case in all current studies) produces a biased estimate (-10.7% versus -5.5%).

There are distinct differences in both the mean and distributional effects of STC when firms differ in workforce stability or by whether they receive a pure subsidy, but they do not differ by industry. If we distinguish firms based on their degree of workforce stability, column 1 of table 6 reveals that the STC program is only effective for cyclically unstable STC firms (panel 3). On average, the STC effect for cyclically stable firms (panel 2) is zero, but it is about 14% for cyclically unstable firms. Moreover, the distribution of estimates for unstable firms (with middle half ranging from -26.4% to -1.9%) is shifted to the left of the distribution for cyclically stable firms (ranging from -8.2% to 7.3%). In regard to industry, columns 2 and 3 show that manufacturing firms, despite being popular STC users, do not seem to benefit more from STC than firms in other industries, whether firms are cyclically unstable or stable. For clarity, we present figure 4 to show that the distribution of STC effects for manufacturing firms is hardly distinguishable from that for non-manufacturing firms. Our findings also suggest that STC has the greatest effect on cyclically unstable firms that are subsidized (from being imperfectly experience rated). Among cyclically unstable firms, STC firms that receive a subsidy reduce their layoff rates by nearly 25% on average (panel 3, column 4), whereas the mean effect is statistically insignificant for those not subsidized. Also, the middle half of the distribution of STC effects for subsidized unstable firms narrowly range from -28% to -22.7%. So, in keeping with Van Audenrode (1994), the STC program's success depends on its generosity, that is, the extent firms share in the cost of its provision.

Earlier we predicted that high-wage firms are likely to incur greater human capital losses and as such are more inclined to make work-hour adjustments to retain valuable workers. Since the STC program works best for subsidized unstable firms, we analyze the role of wages on the effectiveness of STC among these firms. Figure 5 clearly shows a positive association between wage per worker and the extent to which STC averts layoffs. At low wage levels, STC effects tend to be insignificant (shown by the gray plots). However, when wages are in the mid to high range, STC can reduce the layoff rate by 20-35%. Thus, the STC program is most effective when subsidized unstable firms incur significant labor costs. Indeed, such asymmetric benefits may account for why take-up rates are lower than many expect thus solving a paradox in the current literature.

7 Conclusion

This paper estimates the impact of the US Short-Time Compensation (STC) program on the layoff rates of STC firms. Theoretical predictions and the dearth of extant research suggest that the effect is indeterminate and potentially heterogeneous. To address selectivity issues, we compute probability weights for sample attrition and selection into STC, both of which depend on firms' cyclical sensitivities as determined from a finite mixture model. We also check for robustness to unobserved factors that could drive our estimates to zero.

If we presuppose a constant STC effect, our estimate is just about -10%. This estimate is close to the early US evaluation study of Kerachsky et al. (1986). However, that study does not account for potentially important heterogeneous effects, not examined in other studies. We predicted that the effect of STC varies by the extent of cyclical workforce stability, industry, labor costs (a proxy for human capital losses to the firm) and whether firms receive a pure subsidy (i.e. imperfectly experience-rated). Allowing for this heterogeneity, as supported by a model specification test, indicates the cyclically unstable (and not the typical) STC firm benefits from about a 15% reduction in its layoff rate. Moreover, the STC program has the greatest effect on layoff rates among cyclically unstable firms that receive a pure subsidy and potentially face significant human capital losses from layoffs. For cyclically stable firms, we find that the program has no effect, which implies that jobs covered under STC would have been retained even in the absence of the program. Interestingly, we also find that the use of STC by manufacturing firms is no more effective at reducing layoffs than in other firms. Most importantly, the heterogeneous effects we observe could explain the scant take-up rates for the program.

If the only concern is layoff unemployment, our study provides conditional support for the newer compensated work-sharing provisions passed in February 2012 to expand the STC program. This provision, in part, allows for full federal financing of STC benefits for up to three years in states that have an approved STC program. These states can then choose to relieve firms of tax charges for STC benefits paid out (Abraham & Houseman, 2014b). Our findings suggest that such subsidies to cyclically unstable firms with high labor costs (or human capital losses), in the face of relatively low demand, can yield the greatest unemployment reduction benefits.

Table 1: STC program features by sample states in early 1990's

State	Min. number of workers affected	% reduction in hours allowed	Maintain Fringe Benefits	Duration of benefits (weeks)	Exclude part-time or Seasonal workers
California	10%[a]	≥ 10	No	No limit [b]	No
Florida	10%[a] or ≥ 2	10 to 40	No	26	Yes
Kansas	10%[a] or ≥ 2	20 to 40	Yes	26	Yes
New York	5	20 to 60	Yes	20	No
Washington	No Min	10 to 50	Yes	26	Yes

Notes: [a] Proportion of employment at firm or affected unit. [b] No limit on weeks, but total paid cannot exceed 26 x weekly benefit amount. Source: Needels et al. (1997).

Table 2: Descriptives of outcome and covariates for STC and non-STC firms

Variables	**All Firms Mean**	**All Firms SD**	**STC Mean**	**Non-STC Mean**	**Diff P-value**
Layoff rate in 1993 (%)	12.5	15.3	13.8	11.8	0.003
Compensated unempl. charges (%)[a]					
in 1991	1.7	2.2	2.0	1.5	0.000
in 1992	2.4	3.1	3.0	2.0	0.000
No. of employees per firm					
in 1991	61.8	106.7	78.8	52.8	0.000
in 1992	60.5	116.9	74.7	53.1	0.000
Log. avg. wage per worker in 1992	10.1	0.5	10.2	10.1	0.366
UI Tax rate (normalized)	0.44	0.49	0.54	0.38	0.000
Purely subsidized (%)[b]	24.5	43.0	31.5	20.9	0.000
Net balance (1991 – 1992) (%)[c]	−5.1	11.3	−8.0	−3.6	0.000
Industry (%)					
Mining/construction/agriculture	9.0	28.6	9.8	8.6	0.318
Manufacturing	45.1	49.8	50.2	42.4	0.000
Wholesale trade	8.6	28.0	7.1	9.4	0.050
Retail trade	7.6	26.5	6.4	8.2	0.123
Services	23.5	42.4	22.6	23.9	0.467
Other	6.2	24.2	3.8	7.5	0.000
State (%)					
California	29.1	45.4	27.3	30.1	0.153
Florida	14.6	35.3	11.0	16.5	0.000
Kansas	6.7	25.1	6.0	7.1	0.282
New York	35.2	47.8	38.2	33.6	0.027
Washington	14.3	35.1	17.6	12.6	0.001
Number of firms	2420		836	1584	

Notes: [a] Compensated unemployment charges are total (STC and UI) benefits charged to firms are divided by full-time equivalent payroll (total wage plus 2 times the sum of the regular UI benefits and STC benefits, assuming a replacement rate of 50%). [b] Purely subsidized firms are those at the minimum/maximum UI tax rate. [c] Net balance is the difference between the average tax contribution of firms to the UI trust fund over 1991-1992 and the benefits paid out as a percentage of average taxable wage over 1991-1992.

Table 3: A check for balance in covariates between STC and non-STC firms

	Common Support			**No Common Support**		
	Weighted Mean			**Unweighted Mean**		
Covariates	**STC**	**Non-STC**	**ASDIFF**	**STC**	**Non-STC**	**ASDIFF**
Log of average wage/worker	10.151	10.164	0.031	10.154	10.134	0.043
Log of Employee per firm (in 1992)	3.500	3.508	0.006	3.525	3.118	0.332
UI Tax rate (normalized)	0.543	0.558	0.032	0.544	0.378	0.351
Net balance	−7.625	−8.191	0.050	−7.951	−3.551	0.382
Workforce stability indicator	0.466	0.464	0.004	0.461	0.335	0.258
Industry:						
Mining/construction/agric.	0.096	0.096	0.002	0.098	0.086	0.042
Manufacturing	0.501	0.495	0.013	0.502	0.424	0.158
Wholesale trade	0.072	0.076	0.013	0.071	0.094	0.086
Retail trade	0.066	0.063	0.009	0.065	0.082	0.067
Services	0.227	0.231	0.010	0.226	0.239	0.031
State:						
California	0.273	0.269	0.010	0.273	0.301	0.061
Florida	0.112	0.113	0.001	0.110	0.165	0.161
Kansas	0.061	0.059	0.010	0.060	0.071	0.047
New York	0.376	0.380	0.008	0.382	0.336	0.094
Average			**0.014**			**0.151**

Notes: Covariates are the main variables used in computing the probability of selection into STC, along with quadratics and interactions with the workforce stability indicator. Weights, when applied to non-STC firms, are the odds of selection into STC. ASDIFF is the absolute standardized difference in means computed as in Morgan & Todd (2008).

Table 4: Estimated constant STC effect on layoff rate

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
β	0.165^{***}	0.044	-0.082	-0.094^{*}	-0.107^{**}
s.e.	(0.058)	(0.060)	(0.055)	(0.049)	(0.050)
Method	OLS + No Cov.	OLS + WSI	OLS + All Cov.	Matching	IPW
n	2420	2420	2420	2353	2353

Notes: In column 1, standard error (s.e.) is robust. Standard errors in all other columns are bootstrapped to account for the uncertainty in estimating group membership based on workforce dynamics and the probability weights (sample attrition and selection). "OLS + No Cov." indicates no covariates are controlled for in a log-link Gaussian GLM, "OLS + WSI" indicates only the workforce stability indicator is controlled for in a log-link Gaussian GLM, and "OLS + All Cov." indicates controlling for all covariates (used to estimate the probability of selection into STC) in a log-link Gaussian GLM. Matching is based on the local linear ridge matching technique, using a cross-validation bandwidth (in an Epanechnikov kernel) of 0.265. IPW is the inverse propensity weight estimator. Estimations of the IPW and Matching are restricted to the region of common support. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Sensitivity of the IPW estimate to an unobserved confounder

d/s	**0.05**	**0.10**	**0.15**	**0.20**
-0.05	-0.100	-0.091	-0.086	-0.084
-0.10	-0.094	-0.083	-0.072	-0.065
-0.15	-0.089	-0.072	-0.058	-0.045
-0.20	-0.082	-0.061	-0.042	-0.022

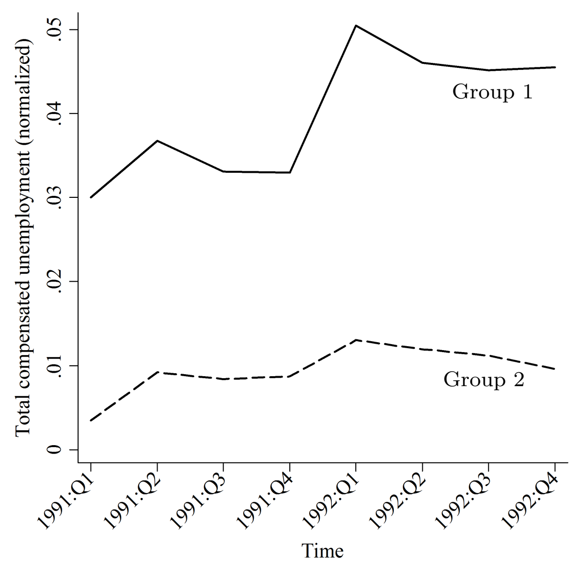
Notes: n=2353. Baseline $\hat{\beta} = -0.107$. The value d is the layoff effect in the program's absence of a simulated unobserved confounder, say 'skill'. The value s is the effect of the simulated unobserved confounder on selection into STC. Estimations are restricted to the common support region.

Table 6: Estimated heterogeneous STC effects on layoff rate

	Overall	**Industry**		**Pure Subsidy**	
		Manuf.	***Other***	***Yes***	***No***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
		Cyclically stable and unstable firms			
Mean	−0.055	−0.046	−0.063	−0.186	−0.013
	(0.055)	(0.057)	(0.054)	(0.079)	(0.064)
P_{25}	−0.144**	−0.120**	−0.173**	−0.268***	−0.094
	(0.059)	(0.060)	(0.061)	(0.093)	(0.061)
P_{50}	−0.071	−0.061	−0.079	−0.218**	−0.014
	(0.062)	0.064	(0.060)	(0.100)	(0.069)
P_{75}	0.047	0.056	0.043	−0.082	0.080
	(0.078)	(0.084)	(0.073)	(0.114)	(0.091)
		Cyclically stable firms			
Mean	−0.003	0.000	−0.005	−0.075	0.009
	(0.075)	(0.075)	(0.076)	(0.121)	(0.082)
P_{25}	−0.082	−0.082	−0.083	−0.082	−0.082
	(0.077)	(0.078)	(0.076)	(0.121)	(0.077)
P_{50}	−0.024	−0.015	−0.030	−0.081	−0.005
	(0.077)	(0.079)	(0.076)	(0.123)	(0.086)
P_{75}	0.073	0.079	0.063	−0.079	0.088
	(0.100)	(0.103)	(0.099)	(0.127)	(0.112)
		Cyclically unstable firms			
Mean	−0.139**	−0.137*	−0.140*	−0.248**	−0.065
	(0.070)	(0.071)	(0.072)	(0.100)	(0.087)
P_{25}	−0.264***	−0.258***	−0.267***	−0.280***	−0.177**
	(0.085)	(0.085)	(0.086)	(0.098)	(0.071)
P_{50}	−0.180**	−0.177**	−0.187**	−0.259**	−0.054
	(0.080)	(0.078)	(0.083)	(0.102)	(0.093)
P_{75}	−0.019	−0.024	−0.014	−0.227**	0.064
	(0.096)	(0.099)	(0.096)	(0.110)	(0.118)

Notes: n = 2353 (906 are unstable firms and 1447 are stable firms). Standard errors are in parentheses and are bootstrapped to account for the probability weights (sample attrition and selection) and the uncertainty in estimating group membership based on workforce dynamics. Estimations are restricted to the common support region. Cross-validation bandwidths corresponding to the variables log average wage per worker, industry, workforce stability indicator, and tax rate (normalized) are 0.424, 0.500, 0.057 and 0.198, respectively. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(a)



(b)

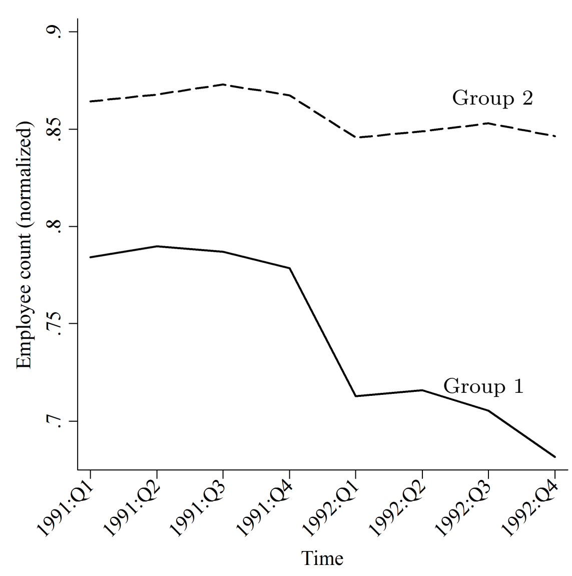


Figure 1: Compensated unemployment and employment trajectories over the period 1991-1992 for each latent grouping of firms identified from a finite mixture model. The lines represent the mean trajectory.

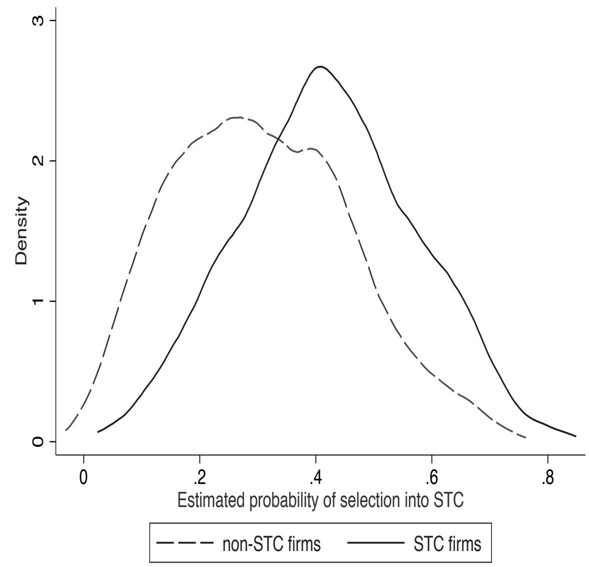


Figure 2: Density plots of the probability of selection into STC among STC and non-STC firms.

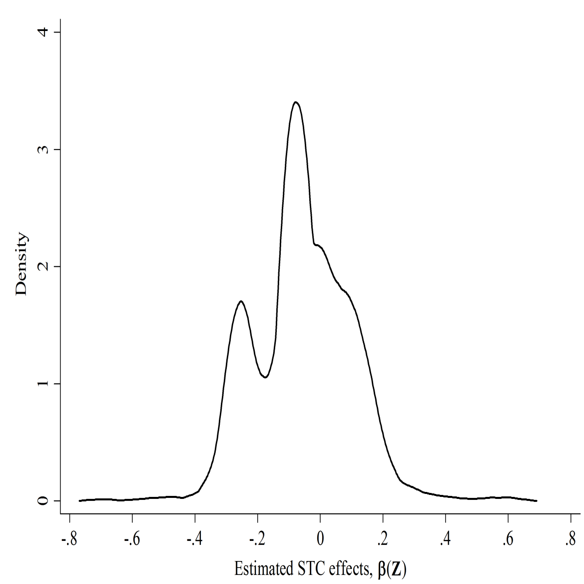


Figure 3: Density plot showing the distribution of the estimated heterogeneous STC effects on layoff rate.

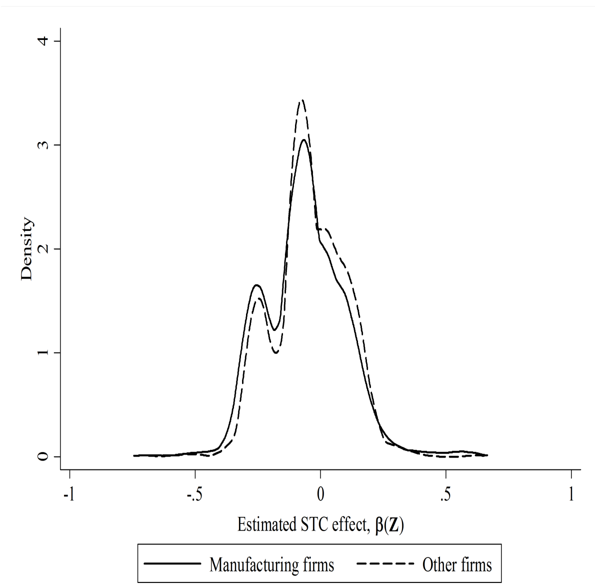


Figure 4: Density plot showing the distribution of STC effects by industry.

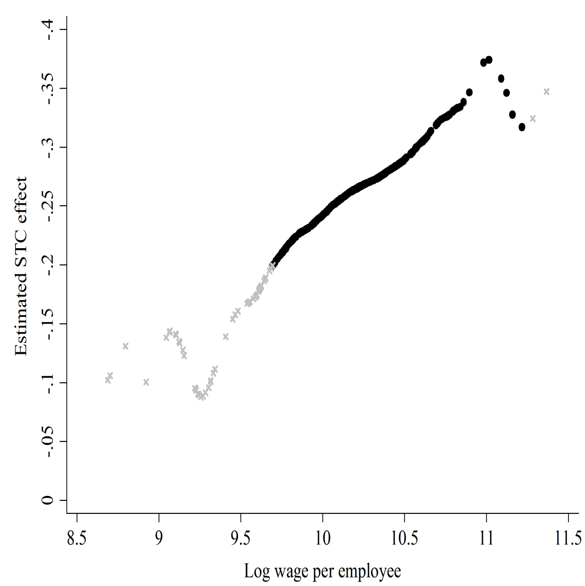


Figure 5: Estimated STC effect on layoff rate as a function of log wage per employee among purely subsidized cyclically unstable firms. Black (gray) plots indicate estimated effects that are statistically significant (insignificant) at the 10% level.

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