CESifo WORKING PAPERS

9469
2021
December 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
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CESifo *Working Paper No. 9469*

Willingness to Pay for Workplace Safety

Abstract

This paper develops a revealed-preference approach that uses budget constrain discontinuities to price workplace safety. We track hourly workers who face the decision of how many hours to work at varying levels of Covid-19 risk and leverage state-specific discontinuities in unemployment insurance eligibility criteria to identify the labor supply behavior. Results show large baseline responses at the threshold and increasing responses for higher health risks. The observed behavior implies that workers are willing to accept 34% lower incomes to reduce the fatality rate by one standard deviation, or 1% of income for a one in a million chance of dying.

JEL-Codes: J170, J220, J280.

Keywords: hazard pay, workplace safety, non-wage amenities, partial unemployment insurance, Covid19, labor supply, value of life.

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December 3, 2021
We are grateful to Elvin Bora for excellent research assistance. We thank Matthew Notowidigdo, Hilary Hoynes and seminar participants at NBER Summer Institute - Labor Studies, NBER COVID-19 and Health Outcomes Conference, Bocconi University, Boston College, EEA-ESSEM, McGill, Barcelona summer forum, SOLE/MEA, North American Meetings of the Econometric Society for helpful comments. We gratefully acknowledge funding from the Block Center for Technology and Society at Carnegie Mellon University and support from the “Adopt a Paper mentoring program”.

1 Introduction

Since the beginning of the economics field, scholars have argued that there are relevant non-wage returns to work. In "The Wealth of Nations," Adam Smith conjectures that "Honour makes a great part of the reward of all honourable professions" (p. 112). Influential subsequent work discusses possible ways to measure the value of such amenities. In perfectly competitive labor markets, amenities will create "compensating differentials," and differences in wages for otherwise similar work can identify the value of such amenities (Rosen, 1986, 1974; Lucas, 1977; Masters, 1969). The empirical implementation of this approach has, however, proven difficult in practice. For one, frictions may prevent that the value of amenities are fully priced into wages. Second, workers typically select jobs with amenities they enjoy, thereby creating additional selection challenges. In this paper, we develop an alternative approach to measure the value of non-wage amenities and apply our approach to the value of workplace safety.

Workplace safety is a canonical case of non-wage work amenities. Every year around 3 million Americans – nearly 2% of the labor force – suffer work-related injuries or illnesses[1] and two recent trends have further fueled interest in worker safety. For one, a growing number of workers are not directly employed by firms but work on their own account as contractors or "gig workers."[2] While wages between gig workers and non-gig workers may be comparable, there are stark differences in the availability of non-wage amenities; in particular, gig workers typically lack access to paid time off and workers' compensation, and are thus more vulnerable to workplace health risks.[3] Second, the outbreak of Covid-19 exposed thousands of front-line workers to health risks at work and sparked a debate about compensation for such risks. Major employers such as Amazon, Best Buy, and Target introduced Covid-19 hazard pay and increased wages for their workers.[4] However, it is unclear how these hazard bonuses were set and whether they fully compensated workers for

[1] Source of injury and illness rates is the BLS series ISU00000000031100

[2] See, e.g., Agrawal et al. (2015).

[3] Studies of earnings in the gig-economy include Cook et al. (2021), Hall and Krueger (2018).

[4] For these companies, the hazard pay ranged between \$2 and \$2.50 per hour (Kinder, Stateler, and Du (2020)). By comparison, in our sample of small businesses hourly wages increased on average by 0.7% (about \$0.13) from the four month immediately before Covid to the four months immediately after within the same employment spells.

the increased risk. More broadly, how do workers value the benefit of safer workplaces beyond Covid-19 risk?[5] And are companies doing enough to protect the health of their employees?[6] This paper aims to address these questions.

Our analysis focuses on front-line hourly workers, mostly in services and retail jobs, who have limited opportunities to work from home and face a choice between risking their health and losing their income. We study their weekly labor supply under varying risk scenarios.[7] Our estimation strategy infers the value of workplace safety from their behavior at budget discontinuities and thus builds on a long tradition of revealed preference studies in economics. The empirical challenge is to generate exogenous variation in the risk-return ratio that credibly identifies workers' preferences. We build on the quasi-experimental approach developed in the bunching literature and use discontinuities in the US unemployment benefit system for this purpose. The intuition is that workers are less responsive to financial incentives when they are mainly motivated to work by non-financial factors such as the enjoyment of the work and colleagues. Conversely, when work produces substantial dis-amenities like health risk or mobbing, the returns to work depend more strongly on financial incentives, and budget discontinuities have an amplified impact on labor supply. Following this dynamic, we show that the excess mass at budget "notches" or similar discontinuities in work incentives can identify worker preferences over non-wage amenities. This approach has thus two advantages. It introduces a quasi-experimental identification strategy to estimate the value of non-wage amenities of work, and it relaxes the friction-less wage setting assumption inherent in compensating differential approaches.[8]

Our application exploits discontinuities in work incentives from partial unemployment insur-

[5] Health is a major source of lifetime income risk: Dobkin et al. (2018) estimate that worker hospitalizations lead to a 20% decline in earnings three years after the initial event.

[6] Workplace safety is particularly deficient in low-paid occupations and labor market inequalities are therefore bigger than wage differences alone suggest. Using Bureau of Labor Statistics data, we calculated that fatality risk for occupations with earnings below the median is 75% higher than for occupations above the median. Sources: TABLE A-5. Fatal occupational injuries by occupation and event or exposure, all United States, 2019, Census of Fatal Occupational Injuries, Bureau of Labor Statistics and May 2019 National Occupational Employment and Wage Estimates, United States, Bureau of Labor Statistics

[7] Our approach is most similar in spirit to Sorkin (2018), who uses job switch patterns to identify non-pecuniary values of firms.

[8] Identification challenges in compensating differential estimates are for instance discussed in Kahn and Lang (1988); Black and Kniesner (2003); Viscusi (2018)

ance rules and the variation in workplace safety during the Covid-19 outbreak. For identification, we use the launch of the Federal Pandemic Unemployment Compensation (FPUC), which creates a jump in workers' budget sets. A worker is entitled to the $600 FPUC weekly wage supplement if her income falls below an earnings threshold, and by moving across the threshold, the worker loses eligibility. State-specific rules lead to 21 different eligibility thresholds – one for each US state that is part of the analysis. As a result of these different eligibility rules, equally paid workers are treated in some states but not in others. We can hence compare two equally paid workers on different sides of the benefit eligibility threshold to identify labor supply responses. Once we identify labor supply, we study how workplace safety affects such behavior.

Our results show a sizable baseline labor supply response to the eligibility threshold for the $600 FPUC. Eligible workers reduce earnings to levels below the unemployment insurance (UI) eligibility threshold, resulting in substantial missing and excess mass in the earnings distribution.[9] We then show that deteriorating workplace safety leads to additional labor supply responses and magnifies the missing/excess mass around the UI eligibility thresholds. For this analysis, we use the large and salient workplace safety shocks during Covid-19 outbreaks. Our measure combines data on local outbreaks with task-specific Covid-19 susceptibility scores. For example, local outbreaks expose restaurant workers to greater increases in risk than workers in automotive repair. The change in workplace risk induced by Covid-19 is sizable and broadly comparable to the change of risks associated with changing from one of the safest to one of the riskiest occupation in the US. [10]

The observed magnified excess mass for higher risk implies that individuals are willing to give up around 34% of their income to reduce Covid-19 fatality risk by one standard deviation, which is equivalent to a decrease of weekly fatalities rates by 31.15 per million workers. Converting the willingness to pay (WTP) into an hourly wage rate, this effect is equivalent to a $6 wage decrease; or it implies that workers are willing to pay 1% of their income to lower their fatality rate by one in a million.

[9]By contrast, in a placebo test, we find no such effects among similar workers who do not qualify for FPUC.

[10]BLS Census of Fatal Occupational Injuries (CFOI) reports that the highest risk occupation in the US is fishing and hunting with a fatality rate of 28 per million workers (converted to a weekly fatality rate), while the lowest risk occupation–educational instruction–has a fatality rate of 0.06 per million workers.

These willingness to pay estimates for workplace safety are higher than the ones obtained using canonical hedonic wage regressions. We apply the hedonic regression approach to our setting and find that a standard deviation in risk is worth 0.5% of income. This is roughly two orders of magnitude less than our baseline WTP estimate. One plausible reason for the difference is the frictions in wage settings; when wages are slow to adjust, they do not fully reflect changes in risk. As a result, frictions in wage setting lead to downward biased estimates in hedonic wage regressions.

We probe the robustness of our identification strategy to several possible threats. First, we consider potential spurious local demand shocks. We use three strategies to investigate such shocks: a placebo test, a border design and a specification which controls for proxies for local demand shocks directly. The results show that such demand shocks are orthogonal to our threshold design and do not bias our results. Next, we address possible spurious changes in labor supply incentives from school closures and find again only minor effects on the results. Finally, we address the impact of selection effects on our results. We run specifications with worker-spell fixed effects and thus hold time invariant firm and worker characteristics constant. Such specifications again yield similar results to the baseline.

We additionally decompose the WTP into a selfish and a prosocial component: the former captures concerns for one's own safety and the latter captures concerns about transmitting Covid-19 to others. The selfish component is more directly comparable with the WTP for non-transmittable illnesses, which do not pose secondary risks for others. Assuming a unitary household with equal utility weight on the health of all members and using the Covid-19 intra-househould secondary fatality rate, we find that pro-social concerns account for a very small part of the WTP estimate, as a result of the relatively limited transmission. Concerns for one's own safety make up the overwhelming majority of the measured WTP, and pro-social concerns account for less than 1% of our estimate.

A central objective of much labor market research is to inform policies around minimum work standards. An influential literature studies the impact of minimum wages; however, minimum standards of non-monetary job characteristics have received far less attention. This lack of studies comes in part from the difficulty of measuring the gains from such non-wage regulations. Our estimates provide a quantitative basis to study the efficacy of workplace safety policies. In a perfectly competitive market, no safety regulation would be necessary, as competition ensures high-risk employers pay high compensating differentials or go out of business. However, with imperfect competition, firms may not fully internalize the cost of high-risk jobs and may expose workers to excessive risks. Our approach provides a method to value such amenities, and our estimates yield a benchmark value for the WTP for safe workplaces. A first-order implication of our work for workplace safety policies is the pricing of hazard pay during the Covid-19 outbreak. Our estimates suggest that hazard pay would need to be as high as \$6 per hour to fully offset the non-pecuniary costs of added workplace risk, a level that is substantially higher than the increases implemented by most employers (\$2-2.5). Our estimates are informative also for pricing risk in non-Covid contexts: reducing workplace fatalities to the level observed in the UK and Germany would lead to substantial gains for US workers. For instance, in construction, such a reform would be equivalent to a 2.5% wage increase, a gain that's similar to the wage effect of introducing a \$15 minimum wage.

To link our results to prior work on the Value of a Statistical Life (VSL), we convert our WTP estimate into a VSL. This approach requires additional data and assumptions. First, VSL assumes that fatality risks are the sole driver of behavior, and second, VSL requires information on the beliefs about fatality risks—here the literature typically assumes that individuals are perfectly informed about risks. Under those assumptions, our benchmark estimates imply a VSL estimate of \$6.9 million, a value consistent with estimates from the literature.[11] In a further contribution, we use data on fatality beliefs to relax the perfect information assumption and show that workers substantially overestimated the fatality risks from Covid-19 and thus acted as if the risk was markedly higher. Failing to account for such imperfect information leads to biases in standard VSL

[11] For recent work on VSL, see for example Guardado and Ziebarth (2019); Lee and Taylor (2019); Lavetti (2020) and for meta-studies on earlier work Viscusi (2018); Viscusi and Aldy (2003).

estimates.[12] Accounting for perceived risk reduces the VSL estimate to $2.6 million.

Related Literature – The topic of non-wage amenities goes back to classic work in economics (this includes Rosen (1986, 1974); Lucas (1977); Masters (1969)), but estimating the value of such amenities is difficult in practice.[13]

The empirical literature on the value of workplace safety typically uses hedonic wage regressions to estimate such values (Lucas, 1977; Brown, 1980; Hwang, Reed, and Hubbard, 1992).[14] Hedonic regressions relate occupational wage differences to workplace risk. A limitation of this approach is that it assumes efficient markets and relies on the idea that the value of workplace safety is priced into wages (Altonji and Paxson, 1992; Bonhomme and Jolivet, 2009; Ruppert, Stancanelli, and Wasmer, 2009). One implication of the efficient labor market assumption is that there is no scope for policy interventions. As a result, hedonic regressions are ill-suited to study policy questions like the optimal level of safety regulation and minimum work standards. For these questions we would need to know the workplace risk that is *not* priced into wages. Our approach allows for potential market failures in pricing the cost of workplace safety into wages, and our estimates can therefore help inform policy decisions on workplace safety.[15]

Another challenge for hedonic wage regressions is to isolate worker preferences from other omitted variables. The canonical hedonic regressions use cross-occupation comparisons: a coal miner, for example, faces greater workplace risk than an administrative assistant, and in a competitive market, this leads to compensating wage differences: a coal miner will earn a higher

[12] Our results echo a sizable behavioral literature on belief formation under uncertainty. See, e.g., classic work on prospect theory by Kahneman and Tversky (1979) and recent work on over-emphasis of salient decision features in Bordalo, Gennaioli, and Shleifer (2013). For empirical evidence, see the review by Robinson and Hammitt (2011) and Viscusi (1990) for an application to health.

[13] Compensating differentials may help explain inequality and rationalize wage differences between otherwise similar employers, which play an important role in the labor market (see, e.g. Card, Heining, and Kline (2013)). Recent applications of the compensating differentials approach to inequality and worker sorting include e.g., Goldin and Katz (2011, 2016); Morchio and Moser (2019); Taber and Vejlin (2020).

[14] For other types of amenities, researchers have also used hedonic regressions (Summers, 1989; Gruber and Krueger, 1991; Gruber, 1994, 1997; Fishback and Kantor, 1995; Stern, 2004). And recent studies pioneered stated preference surveys as an alternative to revealed preference estimates (e.g., Flory, Leibbrandt, and List (2015); Wiswall and Zafar (2018); Maestas et al. (2018)). In addition, Mas and Pallais (2017) use a field experiment to estimate the value of schedule autonomy. Similar experiments with workers' health are, however, undesirable.

[15] Similar to us, Sorkin (2018) also uses a revealed preference approach based on worker decisions rather than wages. He uses this to infer the aggregate value of non-pecuniar amenities at firms.

wage which compensates for the added workplace risk. Unobserved productivity differences make it, however, difficult to separate the role of individual labor supply decisions from confounding factors. Several studies address this challenge by leveraging policy reforms to estimate other non-wage amenities (Summers, 1989; Gruber and Krueger, 1991; Gruber, 1994, 1997; Fishback and Kantor, 1995). We use a similar quasi-experimental approach to estimate the value of workplace safety and leverage budget discontinuities to identify labor supply preferences. The theoretical framework of our work is related to the canonical two good labor-leisure estimation approach (Kleven, 2016; Kleven and Waseem, 2013; Chetty, Friedman, and Saez, 2013), which we expand to a three good economy with workplace safety.

Our work is closely related to a recent stream of work that seeks to provide credible estimates for the value of alternative work amenities (see, e.g., Flory, Leibbrandt, and List (2015); Mas and Pallais (2017); Wiswall and Zafar (2018); Maestas et al. (2018); Sorkin (2018)). Most of these studies focus on stated preferences, while we provide a revealed preference method. Finally, our estimate of a monetary value of avoiding Covid-19 death risk also relates to the large literature on VSL (Prominent examples include Ashenfelter and Greenstone (2004); Viscusi and Aldy (2003)).

2 Partial UI Eligibility and the Federal Pandemic Unemployment Compensation

The quasi-experiment at the heart of our empirical strategy is the launch of the FPUC, a lump-sum $600 expansion of UI weekly benefits paid to all workers on unemployment, independent of the generosity of the UI payment. This reform was introduced as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act, enacted on March 27, 2020, and ended on July 31, 2020.[16]

Employed individuals can receive FPUC payments if they meet the eligibility criteria, including an earnings test that requires that their earnings are below a threshold.[17] Above the threshold,

[16]No FPUC benefits were payable between July 31, 2020, and December 26, 2020. FPUC was re-established by the Continued Assistance Act as a $300 per week supplement to unemployment benefits from December 26, 2020, to March 14, 2021. Please consult Appendix C for more details on FPUC and subsequent programs.

[17]More precisely, FPUC is paid to workers on partial UI benefits. The precise qualifying criteria for partial UI varies

workers become ineligible for FPUC, which generates a notch in their budget set. Figure 1A shows a simplified unemployment insurance schedule and the notch that arises with the launch of FPUC. Ordinary UI benefits are gradually withdrawn as earnings increase and benefits decrease at the benefit reduction rate t with each \$ earned. The \$600 FPUC, by contrast, is not phased out and instead is completely withdrawn once the earning ceiling m^* is reached. Workers thus stand to lose the full \$600 if their earnings exceed m^*. This design creates an incentive not to exceed m^* and potentially generates excess and missing mass in the earnings distribution, as shown by the light grey area in Figure 1B.

The FPUC eligibility threshold m^* is a function of UI benefits and thus vary across workers. Since we do not observe benefits, we use state-specific eligibility rules to compute benefit eligibility and restrict our analysis to workers eligible for maximum weekly benefit (MWB). For the large number of workers in our sample who have a income high enough to qualify for MWB, the earnings threshold and the resulting notch in the budget constraint can be easily computed.[18] For some workers, for whom we only observe an incomplete work history during the qualifying period, we predict eligibility based on full-time earnings at the hourly wage rate of the most recent observed weeks.[19] Since such imputations inevitably introduce noise, we down-weight such observations.[20]

3 Willingness To Pay for Non-Wage Amenities

This section presents a revealed preference approach to identify the WTP for workplace safety by leveraging budget discontinuities. Such discontinuities are typically used to estimate preferences over leisure and income. We extend this framework to a 3 good economy with leisure, income and

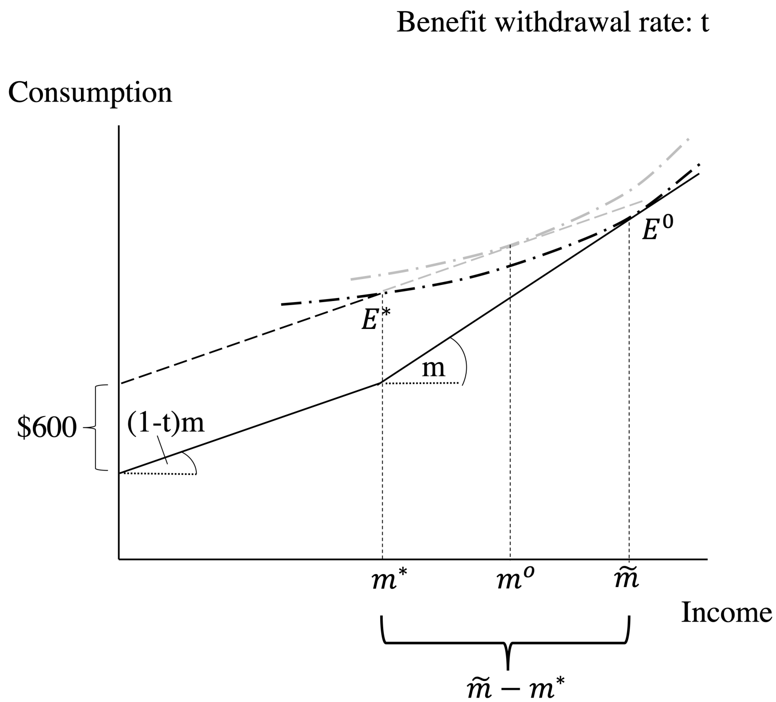
by state. For our sample states, these criteria always include an earnings test. Note that there are typically institutional rules that aim to prevent moral hazard in UI systems. For the most part, UI recipients are not allowed to refuse job offers and job losses should not be due to the fault of the worker. However, these rules are notoriously difficult to enforce and a large literature on UI benefits finds moral hazard problems despite these rules.

[18] To cross-validate the quality of our prediction exercise, in Figure 4B we show that workers who are predicted as not eligible for UI or eligible for thresholds lower than the MWB one exhibit no behavioral response at the notch threshold.

[19] We only use such imputations for the sample selection and they are not needed for the main analysis.

[20] Our weight variable is the share of qualifying earnings that is observed directly in the data. To avoid biases from changing weights, we treat the weights as fixed over time.

Panel A: Labor Supply with Budget Notch



Panel B: Excess and Missing Mass in the Wage Distribution

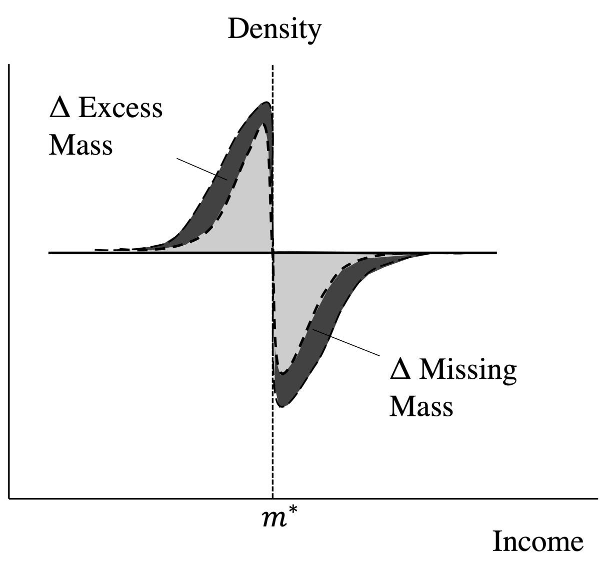


Figure 1: Worker Response to Budget Notch

health.

For an intuition of our approach, consider this simple logic: when non-wage amenities are the main component of returns to work (e.g. workers enjoy spending time with coworkers and the tasks they do), then discontinuities in financial incentives should play a minor role for labor supply decisions. Conversely, when dis-amenities are large, financial returns are the main driver to work, and labor supply should be more responsive to financial incentives. Figure 1B illustrates the implication for excess/missing mass around budget discontinuities. An increase in dis-amenities (in our case, the increase in health risk) magnifies the role of financial incentives, and triggers "magnified excess mass" around the FPUC threshold (illustrated in black). Our proposed empirical strategy quantifies this "magnified excess mass" and thereby estimates how the labor supply elasticity changes when work (dis-)amenities fluctuate. Put simply, we compare the magnitude of excess mass when workplace risks are high and low.

To see this formally, take an individual who obtains utility from after-tax income (or consumption), pre-tax income (cost of effort), and a third good (health in our case). The utility function is $U(m-T(m), m/a, h)$, where m are the earnings, $T(m)$ is the tax schedule, a is the worker ability, and h is the health of the worker. Heterogeneity in ability is captured by a distribution function $f(a)$. Assume this distribution function, the tax system and preferences are smooth so that the resulting earnings distribution is also smooth. The benefit withdrawal rate is t and the benefit Δt is available below earning level m^*. This benefit schedule is illustrated in Figure 1 and is:

$$T(m) = \begin{cases} t * m + \Delta t & m \leq m^* \\ 0 & m > m^* \end{cases}$$

The loss of benefits at m^* generates a notch in the budget that will incentivize movements from the right to the left of the eligibility threshold m^*.

We show how responses at the notch reveal the WTP for workplace safety. We focus on workplace safety, but the same method could be applied to all aspects of work that affect utility (e.g., a sense of purpose, interaction with colleagues, fear of mobbing, etc.). The worker experiences a negative health shock with probability θ during a work hour and the worker's utility in the injured state is $U(m, h_i)$. To simplify notation, we assume that risk increases with income m, rather than work hours, and for a given workday, the health risk is: $r(m) = m\theta$ and the expected utility is:

$$E(U(m,h)) = (1 - r(m))U(m, h_0) - r(m)U(m, h_i)$$

Denote the value of avoiding an injury by W, such that $U(m, h_i) = U(m - W, h_0)$. Analog to the canonical iso-elastic quasi-linear assumption of the two-good economy, we assume that utility is separable and quasi-linear in income.[21] This utility takes the form:

$$U(m,h) = m - T(m) - \frac{a}{1+1/e}(\frac{m}{a})^{(1+1/e)} + h$$

where e is the labor supply elasticity. Using the definition of W, expected utility becomes: $E(U(m,h)) = U(m, h_0) - r(m)W$. Normalizing $h_0 = 0$ we can therefore express expected utility as:

$$E(U(m)) = m - T(m) - m\theta W - \frac{a}{1+1/e}(\frac{m}{a})^{(1+1/e)}$$

The health risk acts like an additional tax with a tax rate θW and reduces the expected return to work.[22] Figure 2 illustrates its impact on labor supply. We can measure the resulting response in the amount of excess mass left of the eligibility threshold. Variation in this perceived tax on work generates fluctuation in the excess mass that identifies W.

To derive an expression for W, we leverage the fact that the marginal worker is indifferent between choosing the notch point m^* and an interior point $\tilde{m}$, $EU^* = E\tilde{U}$. The case is illustrated in Figure 2. At the interior point $\tilde{m}$ the first order condition implies:

[21] The assumption of additive value of amenities is common in the literature (e.g., Morchio and Moser (2019)). For a more general utility function, see Appendix D.

[22] The fact that the implicit tax rate is linear is an artefact of the functional form assumption on the utility. For a more general case the implicit tax is non-linear. In most such cases the linearity can still be used as a local approximation, where the linear tax rate captures W and the local marginal utility of income.

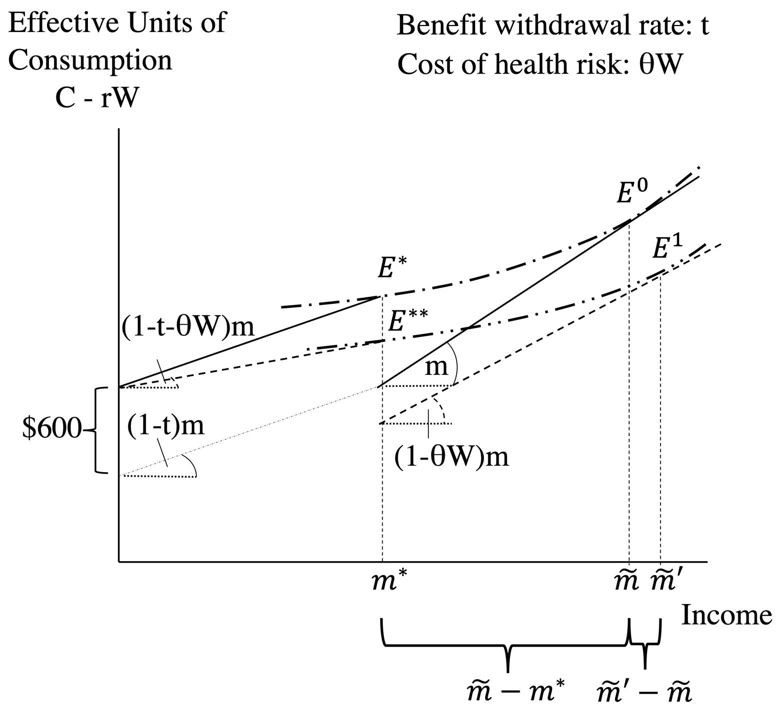


Figure 2: Cost of Health Risk

$$\tilde{m} = a(1 - \theta W)^e$$

and hence $E\tilde{U}$ is:

$$E\tilde{U} = a(1 - \theta W)^{(1+e)} - \frac{a}{1 + 1/e}(1 - \theta W)^{(1+e)}$$
$$= \frac{a}{1 + e}(1 - t - \theta W)^{(1+e)}$$

The utility at the notch point m^* is given by

$$EU^* = (1 - t - \theta W)m^* - \frac{a}{1 + 1/e}\left[\frac{m^*}{a}\right]^{(1+1/e)} + \Delta t$$

Using that $EU^* = E\tilde{U}$ and that the interior solution at the lower tax rate implies $a = m^o/(1 - t - \theta W)^e$, we can obtain the following expression for W:

$$\frac{m^o}{m^*}\frac{1}{1+e}\left[\frac{1}{1-t/(1-\theta W)}\right]-\frac{\Delta t/m^*}{1-t-\theta W}=\left[1-\frac{e}{1+e}\left(\frac{m^*}{m^o}\right)^{1/e}\right]$$

This expression pins down W in terms of measurable quantities $t, \Delta t, \theta, m^*$ and parameters that we can estimate based on behavioral responses: e, m^o.[23]

Without health risk ($\theta = 0$), the previous expression collapses to the standard bunching formula. In all other cases, W is an additional unknown parameter and we require an additional behavioral equation to solve for W. This additional condition comes from observing workers in high and low risk states. The labor supply elasticity in the low risk state is $e = \frac{(\tilde{m}-m^*)/m^*}{\Delta t/(1-t)}$ and in the high risk state: $e = \frac{(\tilde{m}'-m^*)/m^*}{\Delta \tilde{t}/(1-\tilde{t})}$, where $(\tilde{m}' - m^*)$ is the labor supply response in the high risk state and $(\tilde{m} - m^*)$ is the labor supply response in the low risk state. The implicit tax rate in the high risk state is $\tilde{t} = t + \theta W$. We can combine the two elasticity expressions to solve for the willingness to pay for a risk reduction by r (denoted by $WTP(r)$) and express this amount as a fraction of disposable income ($(1-t)m^*$):

$$WTP(r) \equiv \frac{rW}{(1-t)m^*} = \frac{(\tilde{m}'-\tilde{m})}{(\tilde{m}'-m^*)} \tag{1}$$

We arrive at the final expression by using the two previous elasticity expressions and assuming that health risks are smooth throughout the cut-off ($\Delta\tilde{t} = \Delta t$).[24] The final expression states that the WTP is a function of the labor supply response in the high-risk state ($\tilde{m}' - m^*$) and the additional labor supply response in the high state compared to the low-risk state ($\tilde{m}' - \tilde{m}$). Intuitively, the numerator is the labor supply response to an increase in risk and this response is normalized by the labor supply response to a monetary incentive. This allows us to express the WTP in terms of an equivalent $ amount.

Empirically, the additional labor supply response shows up as additional excess mass left of

[23] It can be shown that $(m^o - m^*)$ is closely related to the amount of excess mass created by the budget discontinuity. The link between excess mass (η) and $(m^o - m^*)$ is $\eta = \int_{m^*}^{m^o} d_0 = (m^o - m^*)d_0$, where d_0 is the baseline income distribution. The last equality assumes d_0 is constant and simplifies the expression, the same approach, however, also works for cases with more flexible functions of d_0.

[24] Note that this result holds independently of the structural assumptions about the utility function. The derivation only uses the definition of earning elasticities, which holds for a general set of utility functions.

m^* as illustrated above in Figure 1B. If the excess mass with and without health risk is the same ($\tilde{m}' = \tilde{m}$), then $WTP(r) = 0$. By contrast a large $WTP(r)$ implies that the excess mass increases sharply with risk ($\tilde{m}' > \tilde{m}$). In short, the magnitude of additional excess mass in a high compared to a low risk state identifies the WTP for health in a revealed preference sense.

3.1 Adjustment Frictions

We now consider the impact of adjustment frictions, such as adjustment costs or inattention. Such frictions play a central role in bunching papers that estimate labor supply elasticities from excess mass at budget discontinuities.[25] In principle, any of the methods developed in this literature could also be used to address the impact of frictions on WTP estimates. However, such tools are potentially sensitive to assumptions (Einav, Finkelstein, and Schrimpf, 2017) and WTP estimates can handle frictions in a less parametric way. The WTP is the ratio of two observed responses, and the impact of standard frictions affects the numerator and the denominator proportionally and thus cancels out in the WTP calculation.

First, consider the canonical friction case, where only a fraction α of workers can adjust their labor supply. This will reduce the excess mass (η) at the threshold relative to the friction-less benchmark, and η becomes: $\eta = \int_{m^*}^{m^o} d_0 = \alpha(m^o - m^*)d_0$, with d_0 the baseline income distribution. As a result, multiple combinations of α and labor supply response ($m^o - m^*$) are consistent with the observed η. Note however, that the impact of α cancels out in WTP estimates. WTP is the ratio of excess mass in high (η_H) and low (η_L) risk settings and hence:

$$WTP = 1 - \frac{\eta_L}{\eta_H} = 1 - \frac{\alpha(\tilde{m}^o - m^*)d_0}{\alpha(m^o - m^*)d_0} = 1 - \frac{(\tilde{m}^o - m^*)}{(m^o - m^*)} \tag{2}$$

α affects both the numerator and the denominator proportionally, and hence cancels out. As a result, the WTP estimate is unaffected by the presence of these adjustment frictions.

A second and related friction involves workers who can only choose from a limited number of

[25] The canonical bunching literature has developed tools to identify preferences in a frictional labor market (Chetty et al., 2011; Chetty, 2012; Kleven and Waseem, 2013).

hour options and thus face an an indivisibility constrain. This is for example the case for workers who negotiate hours with their employer and are offered only a few shift options, or cases where workers can add or drop shifts but cannot adjust their labor supply by the minute. These types of frictions create two types of relevant distortions relative to the friction-less case. First, workers may be unable to adjust their labor supply exactly to the threshold, and instead may have to reduce their income below the eligibility threshold. Second, some workers may be deterred from responding to the threshold since the discrete earning options may mean that they could only reduce earnings to a level much below the eligibility threshold and thus would have to accept a larger income cut. Workers are thus less responsive to the threshold than in the friction-less benchmark.

The first challenge is relatively easy to address. The excess mass, η, now spreads over a wider income range and while it may be empirically more difficult to identify the spread out excess mass, such a spread-out mass does not pose any conceptual challenges for our approach.[26] In other words, the first challenge affects the estimation strategy but does not affect the link of the estimates and WTP.

The second challenge can be addressed in a similar fashion as the canonical adjustment friction above. Denote the fraction of individuals who do not respond because of the indivisibility friction by $1-\alpha$. If α is constant, equation 2 applies again and implies that the WTP estimate is unaffected by the second challenge. Our framework thus identifies WTP, even if hours decisions are not fully flexible.

4 Scheduling Data

Our analysis leverages data from a private company, Homebase, which provides scheduling and HR services to small businesses relying on hourly waged workers. Typical businesses covered by the data operate in the restaurant, food and beverage, retail, health and beauty, and healthcare sectors. These are the sectors where most front-line workers are employed, precisely the type

[26]Canonical bunching methods focus on excess mass right at the threshold and would fail to fully capture more spread-out excess mass.

of worker who faces the decision to reduce their work hours to diminish the risk of contracting Covid-19.

The data has three major advantages. First, it provides third-party reported data on weekly work hours and earnings. Obtaining reliable labor supply records has been a key challenge as many survey data sources suffer from measurement errors that make it difficult to accurately measure labor supply changes (see, e.g., classic work by Bollinger (1998); Bound and Krueger (1991)). The Homebase software was created to help companies maintain accurate work hour records: the core feature of the Homebase app is a time-clock app. Workers clock in and out on a mobile phone app when they start and end their shift and the software uses the phone's geo-location to ensure accurate clocking.[27] As a result of these features, we obtain one of the cleanest source of work hours data that we know of and can track work hours and compensation to the minute.

A second advantage of the data is that it covers many states and is available in real-time with daily frequency. Several previous studies of UI benefits use records from the state unemployment administrations, which also have a high degree of accuracy; however, these records often only cover a single state and become available with multiple years of delay. In our case, the data covers 21 states in 2020, which enables us to analyze current policies and control for nuanced state-specific shocks. Relatedly, the Homebase records are not used to administer UI benefits, which alleviates concerns about strategic misreporting and avoidance.

A third advantage is the coverage of the data. The data mainly covers small service sector businesses with hourly workers, which is helpful in our application for two reasons.[28] First, these high-street service sector workers are typically "frontline workers" and are directly exposed to Covid-19 risk at the workplace, which makes this group an ideal sample to study labor supply responses to such risks. Second, adjustment frictions are smaller among hourly workers as their schedules are usually adjusted weekly. This allows for a more precise identification of hour adjust-

[27] When the app recognizes that workers get to or leave the workplace, it sends a check-in/out notification as shown from the app screenshot in Appendix figure A1.

[28] In Appendix B, we systematically compare the Homebase data universe and our analysis sample with a nationally representative survey. That exercise shows that workers in our analytical sample have weekly earnings, hourly wages and hours worked very much in line with the average hourly worker in small firms of the 21 states under analysis.

ments.

A drawback of this type of private-sector data is that we lack data on individuals who exit the sample and therefore do not know whether these individuals left the labor force or changed employers. In our context, this is not a major concern since our methodological contribution is designed to identify intensive margin responses.

Our analysis focuses on the period from November 1st, 2019 until the end of the FPUC program on July 31st, 2020. The period covers four months before and four after the start of the Covid-19 pandemic in March 2020. Finally, since UI eligibility and benefits are calculated based on weekly earnings, we aggregate hours worked and earnings by week for each worker. We restrict the sample to obtain a balanced number of work-week observations before and after FPUC for each worker. This "balanced" sample has two main advantages. First, excess and missing mass are driven by changes within a consistent group of workers and not affected by selection effects.[29] Second, the sample restriction guarantees that any missing mass shows up as excess mass elsewhere in the distribution and excess and missing mass sum to zero by construction. While the sample restriction is not strictly needed, it simplifies both the estimation strategy and the link of the estimates to the theoretical framework.

Panel A of Table 1 shows summary statistics for the workers in our analytical sample. The 6,861 included workers work on average 36 hours and receive weekly earnings of $634. The median hourly wage is $16 and does not vary much (the 25^{th} percentile is $14, and the 75^{th} is $20).

Panel B of Table 1 instead characterizes the 2,771 small businesses included in our analysis sample. On average, they have 1.2 branches and 14.2 employees, of which 97% are hourly waged workers in the median firm. 36% of all firms operate in the Food and Drink sector, with Retail, Health Care and Professional Services being the next most represented sectors in the data.

[29] We select the sample such that each worker has the same number of week spells before and after FPUC but temporary absences (e.g. sickness or holidays) may lead to differences in total weeks between workers. For workers with absences during the sample period, we include the active weeks in the sample, and reduce the number of weeks before and after FPUC to maintain a balanced number of work-week observations before and after FPUC.

Table 1: Descriptive Statistics

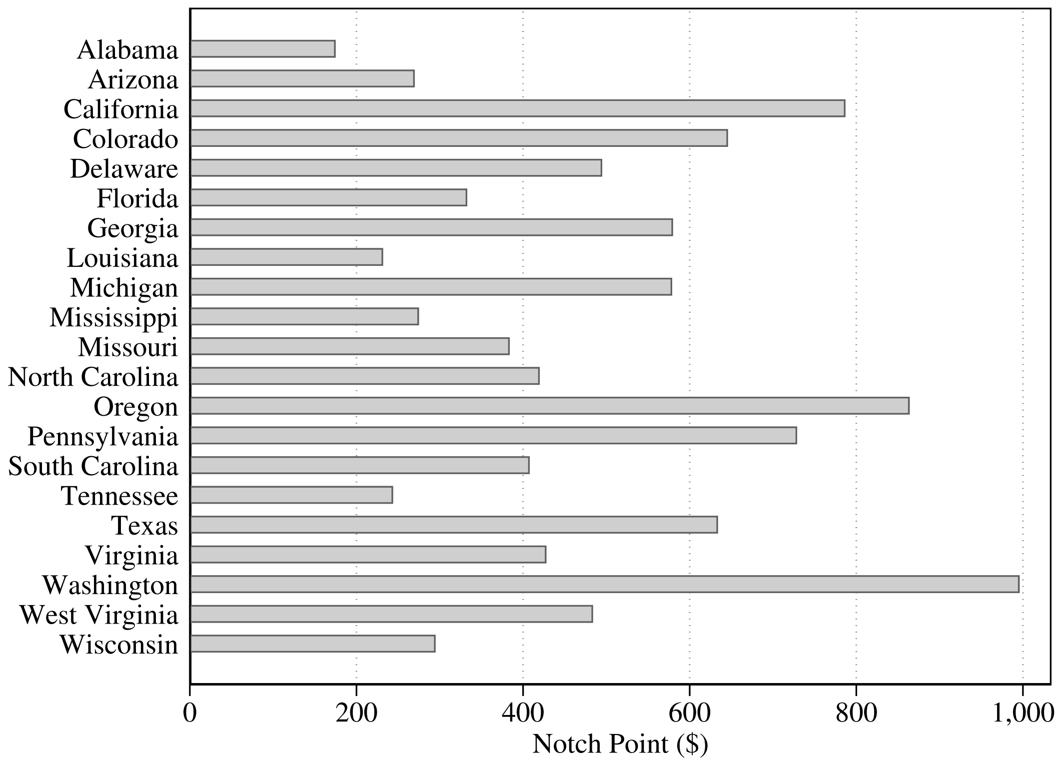
	Mean	S.D.	p50	p25	p75
Panel A: Workers					
Weekly earnings	634.08	332.70	600.01	431.25	780.91
Weekly hours	35.97	13.05	38.19	28.29	44.24
Hourly wage	17.86	7.71	16.00	14.00	19.99
Number of weeks in data per worker	23.35	7.22	26.00	18.00	30.00
Observations (worker-week)	119020				
Number of workers	6861				
Panel B: Firms					
Size	14.18	22.11	8.58	4.58	16.68
Share of salaried workers	0.10	0.16	0.03	0.01	0.13
Number of Branches	1.16	0.70	1.00	1.00	1.00
Food and Drink	0.36	0.48	0.00	0.00	1.00
Retail	0.15	0.35	0.00	0.00	0.00
Health Care and Fitness	0.12	0.32	0.00	0.00	0.00
Professional Services	0.04	0.20	0.00	0.00	0.00
Number of firms	2771				

5 Estimation Strategy

We implement the WTP approach with the notch created by FPUC. A worker is eligible if earnings fall below a state-specific threshold and will become ineligible and lose $600 if earnings move across the threshold. While FPUC was introduced uniformly in all US states, the administration of the benefits was left up to states and states applied different eligibility thresholds. Figure 3 shows the variation across states. A worker earning $400 would be eligible for benefits in California and South Carolina, but not in Arizona or Florida. Our identification stacks these different thresholds to combine 21 difference in difference (DiD) analyses across the sample states.

A key identification challenge is to isolate labor supply response variation from the demand-side effects of the economic crisis and lockdown restrictions that coincide with the launch of FPUC. A standard DiD regression controls for aggregate fluctuations with time fixed effects. One may worry that the recession had different impacts on high- and low-income workers that aren't captured by time fixed effects. To capture such effects, we allow time fixed effects to vary by income

Figure 3: Notch Point by State



Note: The Figure shows maximum allowable earnings while receiving FPUC payments for MWB recipients across US states.

bins. Our analysis compares individuals with identical earnings (held constant with fixed effects for $100 income bins), who happen to fall on different sides of their respective state's eligibility threshold. While the two people may have identical incomes, they face very different labor supply incentives depending on what side of the FPUC threshold they are.

We estimate the following DiD specification:

$$E_{w,t,m,k} = \pi_{m,t} + \sum_{k=-650}^{1300} \beta_k \cdot I_k + \sum_{k=-650}^{1300} \delta_k \cdot I_k \cdot C_t + \varepsilon_{w,t,m,k} \tag{3}$$

where $E_{w,t,m,k}$ is a dummy with value 1 if a worker w is employed in income range m, in week t, \$$k$ away from the UI eligibility threshold, and C_t is an indicator with value 1 after the launch of FPUC. $\pi_{m,t}$ are time fixed effects that vary by $100 income bins and FPUC. Instead of a single FPUC eligibility indicator, we use finer dummies that capture the distance to the eligibility threshold. Theory would predict that responses are starkest close to the eligibility threshold and weaker further away from the threshold. I_k is an indicator that takes value 1 if income is $\$k$ from the UI eligibility threshold and β_k captures the associated excess and missing mass around the eligibility threshold *before* FPUC and δ_k captures the same *after* the introduction of FPUC. Given the controls for absolute income levels with $\pi_{m,t}$, δ_k captures differences in behavior of individuals with identical income, say \$300, but on different sides of the eligibility thresholds. Finally, notice that this set-up turns into stacked difference in difference regressions if $\pi_{m,t} = \pi_t$.

We strengthen the identification strategy in two ways. First, we run a placebo test with workers where our FPUC eligibility threshold does not apply. Such workers are either ineligible for FPUC or face a different threshold. This group shares the same labor market shocks but their work incentives around the threshold are unchanged. We can thus check if there are spurious shocks that generate the observed patterns. Second, we narrow in on the counties at state borders. Such a border design has been used to study the effect of minimum wages (famously by Card and Krueger (1994)) and controls even more flexibly for demand shocks. These border communities generally have integrated labor markets and thus share many of the same demand shocks. Our regressions compare people with identical incomes who work on different sides of a state border, thus facing different UI eligibility criteria.

To implement the WTP approach from section 3, we additionally require estimates of the change in excess mass at different levels of Covid-19 risk. To estimate such effects, we follow two approaches. We first provide graphical evidence of the additional mass by plotting the missing/excess mass separately for five quintiles of Covid-19 workplace risk. Second, we simplify the analysis and provide an estimate for the average excess/missing mass in a \$400 treatment window around the threshold and estimate how this excess mass changes with a continuous risk variable.[30] We implement this by interacting a dummy for the treatment window (T_k) with a continuous risk variable θ. T_k is a categorical variable that takes value 0 outside the $\pm\$400$ treatment window, and inside the window takes value 1 to the left of the threshold (excess mass), and value -1 to the

[30] Results with alternative treatment windows are reported in Appendix A2

right of the threshold (missing mass). For simplicity, we will refer to this as the excess mass, although the coefficient captures both excess and missing mass effects. θ measures workplace risks during Covid-19 outbreaks and we will define it in detail below. The resulting triple interaction specification is:

$$E_{i,t,k,m} = \pi_{m,t} + \delta \cdot T_k \cdot C_t \cdot \theta + \boldsymbol{X\beta} + \varepsilon_{i,t,k,m} \tag{4}$$

where δ captures the impact of higher risk levels on the amount of excess mass at the threshold, $\boldsymbol{X}$ is a vector of the pairwise interactions and single variable entries of T_k, C_t and θ and $\boldsymbol{\beta}$ is the associated vector of coefficients.

6 Behavioral Response to FPUC

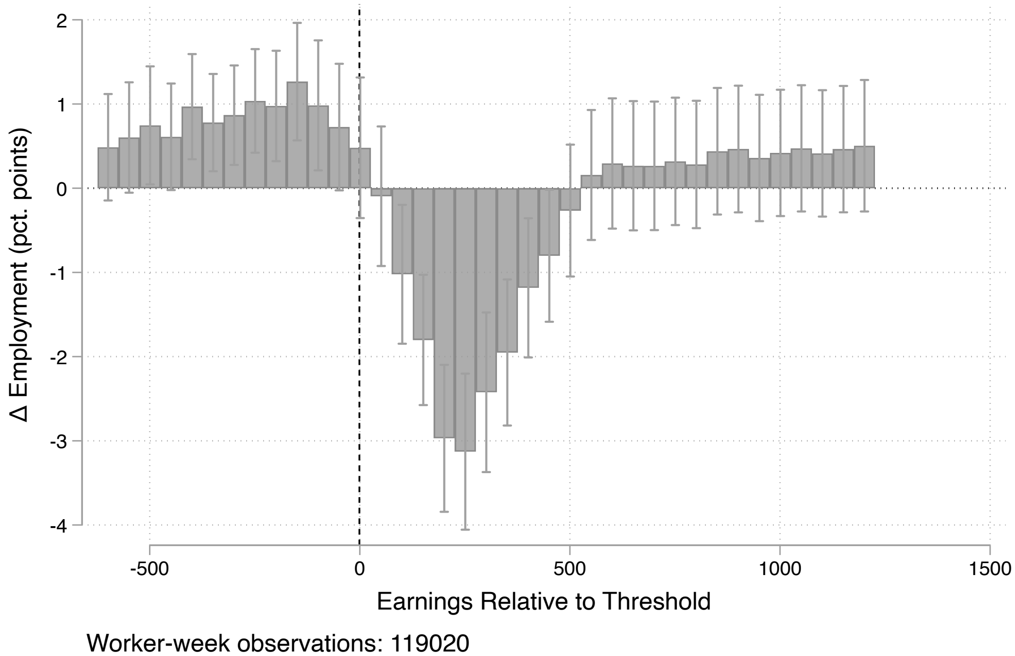
Our first set of results documents the intensive margin labor supply response to the $600 increase in the unemployment benefits available to partially unemployed workers. Figure 4A plots the differences in mass before and after the introduction of FPUC for each $50 bin around state-specific eligibility thresholds. We define these income bins relative to the threshold and normalize the threshold bin to zero, positive bins are thus incomes above the threshold and negative ones are below the threshold. Our results show a sharp response to the increase in UI generosity. Workers move from relative wage bins above the notch to bins below it. The magnitude of these effects is substantial with a missing mass of almost 3 percentage points for the $50 bins with the largest drop (i.e., the bin "threshold+$250"). This corresponds to a 33% decrease in frequency relative to a baseline frequency of around 9%.[31].

A noteworthy feature of 4A is that excess and missing mass are spread out over broader income ranges around the eligibility threshold instead of a single spike right at the threshold. There are several reasons for this. A first factor relates to adjustment frictions in work hours. As discussed in section 3, scheduling frictions may prevent workers from freely choosing their earnings, and could spread their earning responses over broader ranges. A second factor are income effects from the

[31] 9% of all workers in our analytical sample used to work in the bin "threshold+$250" before the start of the pandemic

Figure 4: Excess and Missing Mass around the Partial UI Notch

Panel A: FPUC Eligible Workers



Panel B: FPUC Ineligible Workers

Note: The Figure shows δ_k coefficients from the equation 3. Standard errors are clustered at the state, income bin, week level and 95 percent confidence intervals are reported. In panel a, the sample is hourly workers with sufficient past earnings to qualify for MWB payments in their home state. The baseline mass in the most affected bin is around 9%. In panel B the sample is instead hourly workers with insufficient past earnings to qualify for MWB payments in their home state.

FPUC benefits, which also result in a more spread-out excess mass.[32]

In Table 2 Column 1, we condense the graphical evidence of Figure 4A into a single estimate that summarizes the average excess/missing mass within a $400 treatment window around the threshold, as described in section 5. This estimate shows an average excess/missing mass of around one percentage point.

A potential concern with the setup is that we could pick up differential labor demand shocks, even after controlling for earning level-specific time effects. Note, however, that any such spurious shock would have to be correlated with the state-specific FPUC thresholds. In other words, shocks only pose a threat if they affect specific income ranges and different ones in different states in ways that correlate with the state specific thresholds. We produce a range of robustness checks to analyze this possibility.

First, we repeat the analysis for workers who are ineligible for the benefit at the MWB eligibility threshold. This group has no incentives to respond to the benefit eligibility thresholds on which we focus and we can thus use this group for a placebo test. The results are shown in Figure 4B, which plots the behavioral response around the eligibility threshold for ineligible workers. The effects are insignificant and small in magnitude, confirming that there are no spurious shocks and that our baseline findings for eligible workers reflect responses to the benefit threshold.

Second, we introduce additional controls for demand shocks. We allow such shocks to affect different income ranges in different states by interacting state dummies with a continuous earning variable in the Covid-19 period. These state specific income trends capture broader state-specific shifts in the earning distribution. At the same time, we can still identify our effect of interest through local shifts in the earning distribution around the FPUC threshold. The estimation results remain close to the baseline (approximately 1 percentage point) and thus confirm that our findings are orthogonal to state-specific demand shocks (Table 2 column 2). Next, we allow for even more

[32] Another potential reason is that we do not measure the eligibility threshold accurately for some workers. Differences in observed earnings and UI relevant earnings arise in some jurisdictions from allowances for families or special circumstances or from multiple jobholders. Such factors are typically small and unlikely to affect bins outside the bins immediately at the threshold. As described above, we mitigate the potential impact of this channel by down-weighting cases where we cannot measure benefit-relevant incomes well.

local shocks and repeat the exercise with county-level fixed effects and again find that such controls do not affect our results (column 3). Finally, we also control for industry and individual-specific shocks and again find similar results to the baseline (columns 4 and 5).

To provide further evidence of the absence of potential demand-driven confounding factors, we narrow our analysis to adjacent counties sharing a state border. In such a setting, empirical identification relies on comparing equally-paid workers across state borders with different incentives: such workers are likely to face similar demand shocks, however, one might be eligible for UI while the other might not, simply because of differences in the pre-determined exogenous eligibility thresholds. Our data covers border stretches at 16 state-pair boundaries (see Figure A4). Our results based on the border counties align with the baseline estimates and add further evidence that we are not picking up spurious demand effects (see Appendix E).

7 Willingness To Pay for Workplace Safety

We now use equation 1 to estimate WTP. The denominator of equation 1 is the baseline response discussed in the previous section. The numerator is the additional response when fatality rates increase. To estimate this, we now study how excess mass changes with change in fatality rates.

7.1 Measuring Covid-19 Exposure

To implement this approach, we need a measure of workplace safety that is orthogonal to local worker decisions. We construct such a measure of Covid-19 exposure by combining time-invariant task risk information of industries with data on local outbreaks. The measure thus interacts the vulnerability of a profession to Covid-19 outbreaks with outbreaks in the vicinity of the workplace. We denote the time-invariant riskiness of industry i by I_i and the fatality rate in the c' neighbor counties of c by $F_{c',t}$.[33] Our measure of exposure combines the two:

$$\theta_{i,c,t} = F_{c',t} \cdot I_i \tag{5}$$

By focusing on outbreaks in neighboring counties (c') we can address potential reverse causality issues. Consider, for instance, a case where high WTP workers introduce additional Covid mitigation measures, which in turn reduce local fatality rates. This scenario would lead to a spurious negative correlation between outbreaks and WTP and would bias our estimates downward. We can mitigate such reverse causality issues by focusing on fatality rates in neighboring areas. In practice, the results are similar with fatality rates from c or c', which suggests that reverse causality is not a major concern in our setting. To provide further re-assurances against spurious selection into high and low risk scenarios, we also present results with individual fixed effects which study the same individual in high and low risk scenarios. Note that we focus on fatality rates – rather than infection rates – to measure risks because the lack of testing capabilities at the start of the pandemic resulted in a lack of reliable infection data during the first months. The industry risk I_i is obtained by combining task-specific infection risk data from Basso et al. (2021) with American Community Survey data on the distribution of tasks across industries, and then computing a risk score for each industry.[34]

Since $\theta_{i,c,t}$ has no natural units, we normalize this variable to start at 0 and have a standard deviation of 1. As a result, regression coefficients on this variable capture the effect of an increase in risk by one standard deviation. To provide an interpretable scale for this variation, we calculate the relation between our exposure measure $\theta_{i,c,t}$ and actual fatality rates.[35] One standard deviation of

[33]Appendix F additionally presents results for the two alternative sources of variation (the simple cross-industry variation I_i and variation in local Covid-19 outbreaks within each county $F_{c,t}$).

[34]Basso et al. (2021) use O*NET data to compute task-specific risk measures based on proximity to others at work and the possibility of working remotely. The risk scores are reported at the occupation level and we compute industry averages for the lowest digit industries available in the ACS (mostly 3 and 4 digit) by taking an employment weighted average of occupational risks in each industry.

[35]Data on weekly local industry specific death rates are not available. We therefore rely on county/week death counts ($F_{c,t}$) and compute the death counts in each industry by apportioning the deaths to industries based on time-invariant fatality rates in industries and based on the employment share of the industry ($\frac{e_{i,c}}{\sum_i e_{i,c}}$). For example, a worker in an industry with twice the fatality rate gets a weight of 2, and we therefore assign twice as many deaths to

workplace risk $\theta_{i,c,t}$ is equivalent to an increase in fatality rates by 31.15 fatalities per million workers. This variation is substantial, but in the same ballpark as the pre-Covid-19 cross-occupation variation in fatality rates: one standard deviation in fatality rates across US occupations is 4 cases per million workers per week with the highest risk of 28 for fishing and hunting workers.[36]

7.2 The Value of Workplace Safety

We now estimate how the response to FPUC thresholds varies at different levels of risk and estimate equation 4. We split $\theta_{i,c,t}$ into five quintiles and estimate the responses separately for those five risk levels.[37]

We find that excess mass does indeed increase with $\theta_{i,c,t}$. Figure 5 plots the response to FPUC for the five risk quintiles. The benchmark response in the lowest risk quintile is shown in grey and riskier quintiles in black. In the top left panel, the black area represents the response among workers in the second lowest risk quintile. Despite the relatively low risk, it is visible that such workers are responding more to the FPUC threshold than in the low risk setting. As before, we are controlling for demand shocks with income range specific time effects. The remaining three panels show how the response gets magnified at higher fatality rates. The excess mass is particularly pronounced for the top risk quintile, consistent with the model prediction that dis-amenities at work magnify the excess mass at budget notches.

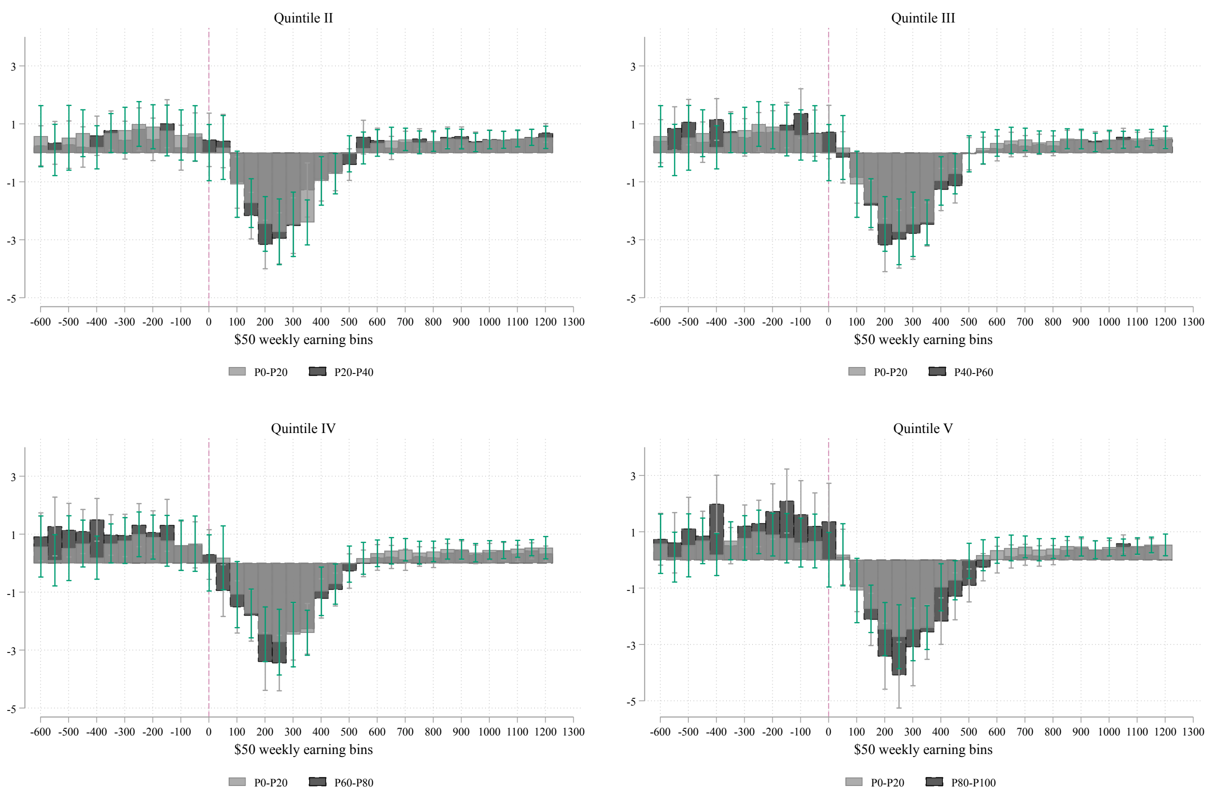
Our Covid-19 risk measure $\theta_{i,c,t}$ is correlated with other shocks to the labor market, yet this does not necessarily pose an identification threat. We are not estimating the general effect of $\theta_{i,c,t}$ but rather the differential impact of $\theta_{i,c,t}$ on the income range around the UI thresholds. Formally, other local shocks only produce omitted variable bias (OVB) if two conditions are met: first, there

the industry relative to the average industry. This exercise requires data on industry specific fatality rates (w_i). Such data are not available at the national level and we instead use data from California, for which such rates are published by Chen et al. (2021). Employment counts come from the ACS 2014-2018. Combining all these steps, our proxy for local industry specific fatality rate is $D_{i,c,t} = F_{c,t} \frac{e_{i,c} \cdot w_i}{\sum_i e_{i,c} \cdot w_i}$

[36] Source: BLS Census of Fatal Occupational Injuries (CFOI) - Current.

[37] A more parametric alternative would interact UI thresholds with a continuous measure of $\theta_{i,c,t}$, which yields similar results. Splitting the data into five quintiles allows for more flexible non-linear effects and provides a more transparent look at the data.

Figure 5: Excess and Missing Mass around the Partial UI Notch by Fatality Rates



Note: The Figure shows $\delta_{k,\theta}$ coefficients from equation 4. Results for 5 quintiles of Covid-19 risk (θ) are plotted. The gray bars represent the response in the lowest quintile and black bars in the sub-panels respectively show responses in risk quintiles 2 to 5. The sample covers hourly workers with sufficient past earnings to qualify for MWB payments in their home state and is based on 119,020 work-week spells. Source: Homebase.

are omitted variables which correlate with the treatment variable–clearly the case here–and second, these variables are also correlated with the outcome variable. Our outcome of interest is excess mass at UI thresholds and our identification assumption is that demand shocks are "smooth" around the thresholds. Our identification assumption is thus based on the second OVB condition. Since we have many different thresholds, we can relax the identifying assumption further and assume that shocks can be non-smooth, as long as their impact is similar across states. We can absorb the effect of shocks from their average impact across states and identify the impact of the UI threshold from the changes near the location specific FPUC threshold. Notice that our identifying assumption is similar to canonical bunching estimators, which also assume that demand shocks are smooth around the threshold. In other words, WTP can be identified when the identifying assumptions for canonical bunching estimates are met. Importantly, we do not require that $\theta_{i,c,t}$ is uncorrelated with demand shocks, any such shock that is orthogonal to the state specific thresholds will not affect the results.

To probe whether this identification assumption holds, we again run a placebo test with FPUC ineligible workers. Figure A3 repeats the analysis for workers who have no incentives to respond to the MWB eligibility threshold. We don't find any spurious effects in the placebo sample, which adds further confidence that the research design is indeed picking up labor supply responses.

We now use these results in equation 1 to compute the WTP for workplace safety. According to this equation, WTP is the ratio of the baseline response to FPUC and the additional labor supply response created by workplace risk (seen, respectively, in Figure 4 and 5). For the WTP estimate, we now summarise the excess mass shown in these figures with specification 4, which estimates the average excess mass in a \$400 treatment window around the threshold.[38] Panel A of Table 2 reports the results for the denominator of equation 1 and shows that FPUC creates an excess mass of around one percentage point in the income bins surrounding the earnings threshold. Panel B shows results for the numerator – changes in excess mass as workplace risks increase. A standard

[38] In Figure A2 we test the sensitivity of our DiD estimate to changing treatment windows around the threshold. Our estimate is statistically significant if we consider a window of \$150 around the threshold. We identify only a subset of the response if we focus on a narrow window: once the window is \$250 or bigger, the effect is very stable.

deviation increase in risk leads to 0.35 percentage points more excess mass. Combining these results we find that the implied willingness to pay is therefore between 31% and 34% of weekly income, or around \$216. Expressed in terms of fatality rates, this implies that workers are willing to pay around 1% of their income to cut weekly fatality rates by one per million (Panel C).

Table 2: Willingness To Pay for Workplace Safety

	(1)	(2)	(3)	(4)	(5)
		Panel A: Baseline Excess Mass			
FPUC	1.044	1.044	1.044	1.044	1.044
	(0.102)	(0.104)	(0.104)	(0.102)	(0.104)
		Panel B: Additional Excess Mass			
Workplace Risk std. dev.	0.353	0.330	0.328	0.347	0.325
	(0.0565)	(0.0553)	(0.0554)	(0.0561)	(0.0555)
		Panel C: WTP (% of weekly income)			
Workplace Risk (std. dev.)	33.8	31.6	31.4	33.2	31.1
Workplace Risk (deaths per mio.)	1.1	1.0	1.0	1.1	1.0
		Panel D: Value of Statistical Life (million \$)			
VSL (perfect information)	\$ 6.89	\$ 6.44	\$ 6.40	\$ 6.78	\$6.34
VSL (actual information)	\$ 2.60	\$ 2.43	\$ 2.42	\$ 2.56	\$2.40
FE, interacted with income x time FE		state	county	industry	individual

Note: The Table shows how Covid-19 risk affects excess mass at the FPUC eligibility threshold. Panel A shows excess mass around the FPUC threshold for average risk from estimating equation 4 with $\delta_{k,\theta} = \delta_k$. Panel B, shows how excess mass changes with fatality rates ($\delta_{k,\theta}$). Willingness to pay in Panel C is based on equation 1, and is the ratio of panel B and panel A. Panel D computes $VSL = \frac{WTP}{\Delta fatality} * m$, where m is income. And one standard deviation of workplace risk increases fatality rates by 31.15 cases per million workers and beliefs about fatality rates by 82.33 cases per million workers. Controls are state, county and two digit NAICS fixed effects, interacted with a dummy for the Covid-19 period and a continuous income variable. The results are based on 119,020 worker-week spells. Source: Homebase, Chen et al. (2021).

We then explore the robustness of these results. In columns 2 to 5, we repeat the sequence of controls described in section 6. First, we interact county and state FE with time effects and income to capture local demand shocks (columns 2 and 3). In these specifications, we exploit the remaining cross-industry heterogeneity in $\theta_{i,c,t}$. In appendix G we additionally show that our results hold when we explicitly control for proxies of local labor demand shocks and local policy changes, providing further evidence that the threshold design separates labor supply effects from confounding local shocks.

Another potential challenge are selection effects. Those have been a central concern in the context of canonical hedonic wage regressions. The concern is that when amenities are normal goods, individuals with higher ability and earning will purchase more amenities but still have higher earnings left. As a result wages and amenities look positively correlated and bias hedonic regressions. Our approach can tackle this issue in two ways. First, we study a sudden and unexpected change in workplace risk, which alleviates concerns that workers may have sorted into risk exposure. Second, our approach relies on changes in behaviour and thus absorbs any time invariant heterogeneity in worker types.

While this addresses canonical selection effects based on time-invariant characteristics, there could still be selection effects from more complex worker characteristics that vary over time. For instance, industries with more exposure to Covid-19 outbreaks might employ workers with systematically different labor supply elasticities, and hence workers may respond differently to outbreaks, not because of differential exposure to risk but because of their differential elasticities. We explore this possibility and allow for industry specific labor supply elasticities by letting the responses to FPUC vary by industry. Specifically, we interact industry dummies with the launch of FPUC and income (column 4). These specifications absorb the baseline response to FPUC by each industry and identify effects of risks from *within* industry variation in risk over time. Next, we control for heterogeneity in elasticities at the more granular individual level. To go beyond conventional time invariant individual fixed effects and absorb the time varying impact of heterogeneity in labor supply elasticities, we again interact the fixed effects with the launch of FPUC and income. These fixed effects absorb the individuals' average labor supply change from before to after FPUC and thus identify responses to risk from changes in the same individuals' behaviour in high risk versus low risk settings (column 5). Throughout all these robustness tests the results remain close to the baseline.

8 Discussion

8.1 Comparison with Hedonic Wage Regressions

An appealing feature of this setting is that we can compare our approach to the results obtained from canonical hedonic wage estimates. We run a hedonic regression in our data and estimate how hourly wages change with our measure of workplace risk. Individual fixed effects control for time-invariant worker ability and ensure that selection effects do not bias these results. We find that wages are broadly unchanged by workplace risk and the point estimate is insignificant. The point estimate is also quantitatively small and suggests that wages increased by 11 cents with one standard deviation of $\theta_{i,c,t}$, which corresponds to a 0.5% wage increase (results are not reported but are available upon request). This small coefficient likely reflects the fact that wages are slow to adjust and, despite several high profile examples of hazard pay, unlikely to fully price in changes in workplace risks. These estimates would lead us to conclude that workers attach next to no value to workplace safety. Our approach, by contrast, suggests that these low estimates are biased. Workers do indeed respond substantially to workplace risks and our estimate implies a WTP that is an order of magnitude greater than the hedonic result.

8.2 Workplace Safety Policy

During the Covid-19 crisis, several companies introduced hazard pay that aimed to compensate frontline workers for the added risks they faced. Critics of hazard pay argue that these rates were too low and did not fully compensate for large risk exposure. Our estimates shed light on this debate and quantify the non-pecuniary value of Covid-19 risk exposure. We do indeed find that hazard pay rates were lower than the implicit cost of risk exposure. To fully offset the non-pecuniary costs of added workplace risk, hazard pay for a standard deviation increase in risk would need to be as high as 34%, or \$6. In practice, big retailers introduces hazard rates between \$2 and \$4 dollars, with smaller or no bonuses in most small businesses. In other words, workers were worse off at work during Covid-19, despite the introduction of hazard pay.

These results relate to the broader policy debate about workplace safety regulations. Addressing this issue has been challenging, in part because it is difficult to quantify the gains from such non-wage regulations. The rationale for policy interventions is however similar to minimum wage regulation: in imperfect competition, firms may not fully internalize the cost of high-risk jobs and thus may expose workers to excessive risks. In practice, all governments implement some level of worker safety regulation, albeit with large differences in stringency and enforcement. In the design of such policies, the monetary value of improved workplace safety plays a central role and determines the welfare gains from such policies.

Our results suggest that workers value workplace safety highly and that the gains from more stringent safety regulations are substantial. To illustrate this point, we perform a back of the envelope calculation for the construction industry, a large and relatively risky industry. Weekly fatality rates in this industry in the US are 3 workers per million full-time employees per week.[39] Our estimates suggest that eliminating fatality risks would be equivalent to a 3% increase in wages. Reducing risk thus potentially offers large gains for workers. Reducing fatality risks to zero is perhaps an unattainable target. However, even reducing fatality rates to the level seen in the UK or Germany would be a substantial improvement and equivalent to a wage increase of 2.5%.[40] Such gains happen to be similar in magnitude as the worker gains from the introduction of a $15 minimum wage, a popular labor market intervention.[41] Another useful point of reference is the wage gain implied by switching industries. Such an exercise helps evaluate the potential for compensating differentials to explain wage dispersion. The gains from greater safety by changing from the construction sector to the safer accommodation and food services sector are worth around 2.5% of income. Moving to the riskier agricultural sector is equivalent to a wage loss of 8%. The magnitude of these gains are comparable to the value of other work amenities analysed by Maestas et al. (2018), who find values ranging from 2% to 16%.[42]

[39]ILO data is converted to weekly deaths per million workers for comparison. Annual fatality rates are 160 per million workers in 2018. Source: ILOSTAT, series "INJ FATL ECO RT A" 2018.

[40]ILO estimates for Germany and the UK are respectively 0.4 and 0.7 weekly deaths per million workers.

[41]The minimum wage calculation computes the wage floor that is equivalent to a 2.5% mean wage increase (assuming no employment loss). The data source is the 2019 and 2020 CPS ASEC data.

[42]Maestas et al. (2018) study the value of schedule autonomy, telecommute, physical activity, sitting, relaxed work

When generalizing our estimates to non-Covid-19 workplace risk, we need to consider that the WTP for a non-transmissible illness or injury might be lower. Our WTP estimate might in part reflect workers internalizing the risk of Covid-19 transmission to others. The higher the weight workers place on others' health in their utility function, the more likely our estimate represents an upper bound for non-transmissible workplace risk. Conversely, in the canonical case of myopic individuals, who only care about their own utility, the WTP for transmittable and non-transmittable health risks coincide.[43] To get a sense of the importance of the pro-social feature in our WTP estimate, we perform a back of the envelope calculation for a worker who cares about the well-being of other household members. Denote the utility weight of other household members by Ω, the number of other household members by n and the intra-household secondary fatality rate by s. The relation of WTP for a transmittable (WTP_T) and a non-transmittable disease (WTP_{nT}) is: $WTP_T = (1 + \Omega \cdot s \cdot n) \cdot WTP_{nT}$. For the back of the envelope calculation, note that the intra-househould secondary fatality rate is $s = 0.002$ and assume that the worker cares as much about others' utility as her own ($\Omega = 1$).[44] For household size, consider a four person household, i.e. a household at the 90th percentile of the US size distribution. In this case, $WTP_T = 1.006 \cdot WTP_{nT}$ and WTP_{nT} is thus only 0.6% smaller than our baseline estimate. In other words, our baseline estimate of 33.8% would be reduced to roughly 0.338/1.006=33.6% of weekly income for a non-transmittable disease. Quantitatively, the concern for once own health is thus the main component of the WTP estimate, with a quantitatively small additional contribution from pro-social concerns.[45]

environment, work autonomy, PTO, team-work, training, and opportunity to serve.

[43] The prior literature almost exclusively considers myopic agents when interpreting risky behavior of individuals.

[44] s is obtained multiplying the 30% intra-household transmission rate (Lewis et al., 2020) with the 0.68% infection fatality rate, that is the fatality rate conditional to being infected (Meyerowitz-Katz and Merone, 2020)

[45] Pro-social concerns will play a more important role for diseases with more aggressive transmission rates and play a minor role in this setting because s is small.

8.3 Value of a Statistical Life

A popular approach for quantifying responses to health risks is to compute a "value of a statistical life" (VSL). Such estimates infer what implicit value of life is consistent with the observed behavior. Such estimates require additional assumptions: first, they assume that the fear of dying is the sole driver of the observed behavior. Since higher fatality rates are typically accompanied by unpopular safety measures and imply a greater risk of non-fatal injuries, this assumption presumes that workers attach zero value to non-fatal aspects. Second, VSL estimates typically assume perfect information. In other words, it assumes that the true change in risk is known to the decision makers.

If we are willing to make these assumptions, we can compute VSL as the ratio of WTP to the change in fatality risk: $VSL = \frac{WTP}{\Delta fatality}$. Using our estimates, we find $VSL = \frac{\$216}{31.15/1{,}000{,}000} = \$6.9$ million (Panel D of Table 2). A value of \$6.9 million broadly aligns with the literature, a recent meta-study by Viscusi (2018) concludes that VSL is somewhere between \$3 and \$13 million (in 2020 USD). Our results are in line with these findings and are at the middle of this range.

Ideally, researchers would relax the perfect information assumption and compute $VSL = \frac{WTP}{E[\Delta fatality]}$, where $E[\Delta fatality]$ is the workers' perception of fatality risk. Since these perceptions are not usually observed, studies instead use the statistical fatality rates as a measure of perception, thereby imposing perfect information and rational expectations assumptions.[46] During the Covid-19 outbreak, beliefs about fatality risks were collected as part of the Understanding America Study (UAS) and we have a rare opportunity to observe perceptions about fatality risks directly and can thus relax the perfect information assumption.[47] The data covers a representative sample of the US population and uses weekly rounds of interviews. We use this data to compute expectations at the week-state-industry level and then use these to impute expectations for our sample. The expectation measure thus undoubtedly includes measurement error. Our approach can be thought of as an instrumental variable approach that instruments fatality beliefs with our risk measure.

[46] Frequent violations of these assumptions are famously documented in Kahneman and Tversky (1979).

[47] Individuals were asked about their probability of contracting Covid-19 and conditional on this, their probability of dying.

We find that one standard deviation in fatality risk increases expectations of fatality risks by 82.52 deaths per million. The result is highly significant as local Covid-19 outbreaks lead to a sharp increase in the beliefs about the risk of dying. This increase is bigger than the increase in actual fatality risks. People thus overreact relative to a perfect information, rational agent setting. The extensive news coverage of Covid-19 deaths made such risks extremely salient and an in line with the behavioral literature on "salience" (Bordalo, Gennaioli, and Shleifer, 2013). We find that peoples' beliefs overshoot the true changes in risk. Using the perception data for $E[\Delta fatality]$, we find a VSL value of $2.60 million (Panel D of Table 2), about a third of the rational expectation estimate. Perceived fatality rates enter the VSL calculation as the denominator and replacing rational with actual expectations thus increases the denominator of the VSL calculation and lowers the VSL estimate. In other words, accounting for imperfect information implies that the same behavioral response is produced by a larger shock to risk perceptions. This illustrates the importance of accounting for belief sets when evaluating worker behavior. Moreover, persistent high perceptions of risk can potentially explain why workers have been reluctant to return to work and hence why labor supply remained lower when Covid-19 rates fell.

9 Conclusions

This paper presents a new method to identify the value of non-wage amenities based on excess mass responses to varying amenities around budget discontinuities. This approach formalizes the idea that workers will respond less to financial incentives when non-wage amenities are more valuable. We apply this method to measure the value workers attach to safe workplaces. The launch of FPUC produced notches in workers' budget constraints at the partial UI eligibility threshold. We find substantial baseline labor supply response to these notches under no Covid-19 risk. We next estimate how these labor supply responses change with increasing Covid-19 risk and show that Covid-19 risk leads to magnified responses.

The resulting estimates imply that workers are willing to sacrifice 34% of their weekly disposable income to decrease their risk by one standard deviation. This is equivalent to giving up 1% of income to avoid a one-in-a-million risk of dying.

We find that the cost of Covid-19 risk wass not fully priced into wages. Indeed, the Covid-19 hazard bonuses covered only one third of the non-pecuniary cost of working under greater health risk. This evidence has stark implications for WTP estimates obtained using standard hedonic wage regressions. Such estimates understate the true cost of workplace risk by only focusing on the costs that are priced into wages. Policy makers aim instead at targeting the costs of workplace safety that are *not* priced into wages. We show that such costs exist and are sizable.

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A Appendix Figures and Tables

Figure A1: Scheduling App Screenshot

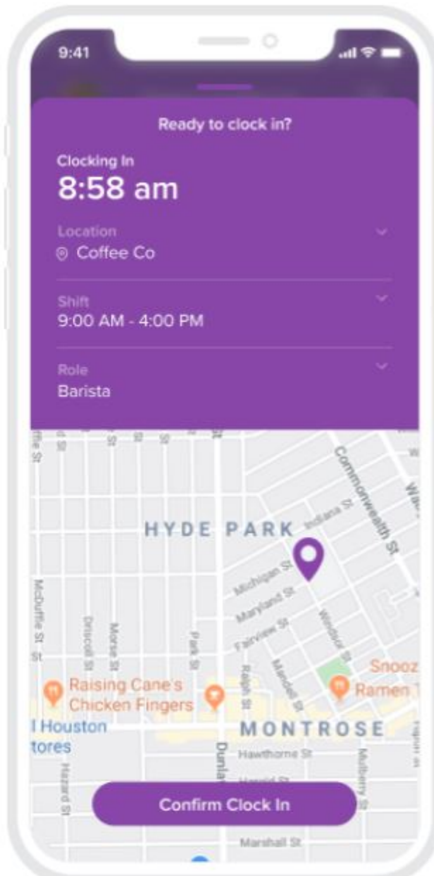
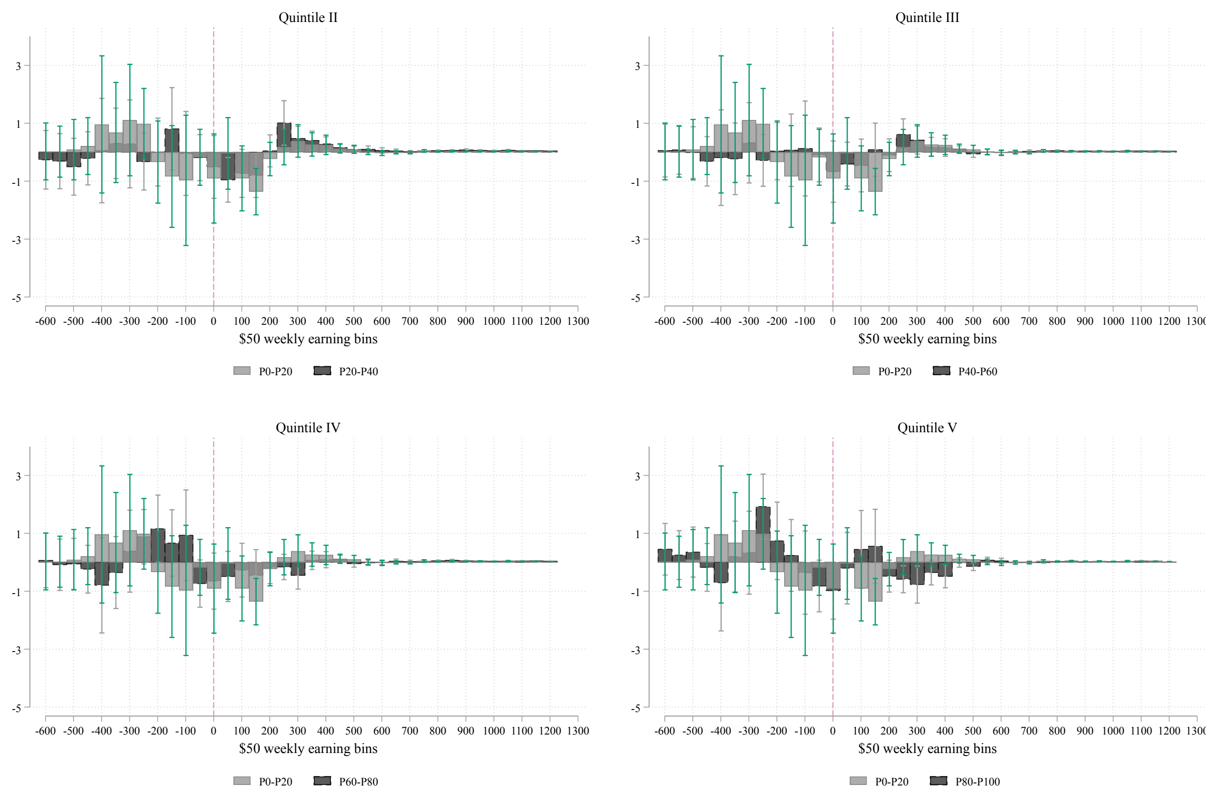


Figure A2: Effect of FPUC with Alternative Treatment Windows

Figure A3: Placebo - Ineligible Workers - Excess and Missing Mass around the Partial UI Notch by Observed Death Risk in County



Note: The Figure shows $\delta_{k,\theta}$ coefficients from equation 4. Results for 4 different Covid-19 risk levels (θ) are plotted in each panel in dark colors. Covid-19 risk is measured as deaths per million in the week in the local area. The light bars are the benchmark response in areas with 0 Covid-19 deaths. The sample covers hourly workers with sufficient past earnings to qualify for MWB payments in their home state. Source: Homebase.

B Homebase Data Benchmarking

Table A1 presents summary statistics for wages, weekly earnings, and hours worked across Annual Social and Economic (ASEC) supplement to the Current Population Survey (CPS), Homebase data, and Quarterly Workforce Indicators (QWI). Summary statistics reported for ASEC combine 2019 and 2020 ASEC supplements. Column (1) presents summary statistics without any restrictions; column (3) restricts ASEC data to the 21 Homebase states; and column (4) applies further restrictions that allow for comparability of ASEC to the Homebase sample. Specifically, the restricted ASEC sample comprises of hourly workers, not self-employed, in small-businesses that correspond to Homebase North American Industry Classification System (NAICS) codes in Homebase states.[48]

Homebase provides 6 digit NAICS codes but ASEC does not provide an industry classification that uses NAICS. Therefore, the industry classification in ASEC is first crosswalked to NAICS using the crosswalk provided by IPUMS.[49] Next, the ASEC sample is restricted to Homebase NAICS codes in a step-by-step manner: if an ASEC industry is linked to a 6-digit NAICS code, it is classified as in the Homebase sample only if it matches a 6-digit Homebase code, and it is classified as not in the sample if it does not match any 6-digit Homebase code. Next, if an ASEC industry is linked to a 5-digit NAICS code, it is classified as in the Homebase sample if it matches the first 5 digits of a 6-digit Homebase NAICS code. This process is repeated until all ASEC NAICS codes are classified and the resulting crosswalk is used to restrict ASEC in column (4).

Column (2) presents Homebase summary statistics without any restrictions, inclusive of 2019 and 2020. Column (5) restricts Homebase to the study sample that comprises of individuals eligible for full UI benefits with a balanced number of week spells before and after FPUC. Appropriate survey weights are applied for each ASEC and Homebase summary statistic.

Column (6) presents QWI summary statistics in 2019, restricted to privately owned small firms with fewer than 20 employees in 21 Homebase states.

Table A2 lists the distribution of observations across different 2-digit NAICS sectors. The same restrictions are applied as in Table A1.

[48]Workers are classified as hourly according to the paidhour variable. Firmsize variable is used to restrict the sample to small businesses with fewer than 25 employees. The classwkr variable is used to remove self-employed workers from the sample.

[49]See "IND AND INDNAICS: CODES FOR INDUSTRY (IND) AND NAICS INDUSTRY (INDNAICS) IN THE 2000 CENSUS AND THE ACS/PRCS SAMPLES FROM 2000 ONWARD" `https://usa.ipums.org/usa/volii/indtoindnaics18.shtml` and "ATTACHMENT 9: INDUSTRY CLASSIFICATION: Industry Classification Codes for Detailed Industry (4 digit) (Starting January 2020)" `https://www2.census.gov/programs-surveys/cps/methodology/Industry%20Codes.pdf`.

Table A1: Summary Statistics: Hourly Wages, Weekly Earnings, and Hours Worked

	(1) ASEC Full	(2) HB Full	(3) ASEC HB States	(4) ASEC Sample	(5) HB Sample	(6) QWI Sample
Hourly wage	18.69	12.41	18.46	16.68	17.86	
	(10.84)	(4.846)	(10.66)	(9.101)	(7.710)	
Weekly earnings	1016.7	377.6	999.6	631.8	634.1	805.5
	(724.4)	(244.6)	(716.1)	(432.3)	(332.7)	(328.4)
Hours usually worked per week	39.25		39.32	35.78		
at all jobs	(11.30)		(11.11)	(11.00)		
Hours usually worked per week	38.55	29.58	38.66	35.13	35.97	
at main job	(10.84)	(13.27)	(10.69)	(10.60)	(13.05)	
Hours worked last week	38.45		38.49	34.84		
	(12.80)		(12.63)	(12.06)		

Note: Mean coefficients and standard errors in parentheses. ASEC and HB Full data include 2019 and 2020. QWI data is 2019 only. Column (3) ASEC is restricted to the 21 HB states. Column (4) ASEC sample is restricted to hourly workers, not self-employed, in small businesses ($<$ 25 employees) corresponding to HB NAICS codes in HB states. Column (5) HB sample is restricted to individuals eligible for full UI benefits (defined as meeting state specific earning requirements in previous quarters) with balanced number of week spells before and after FPUC. Column (6) QWI sample is restricted to privately owned small firms ($<$ 20 employees) in HB states. Weekly earnings are calculated from beginning-of-quarter employment average monthly earnings. Monthly averages are divided by 4.345 to get weekly averages.

Table A2: Weighted Number of Observations across NAICS 2

	(1) ASEC Full	(2) HB Full	(3) ASEC HB States	(4) ASEC Sample	(5) HB Sample	(6) QWI Sample
11 *Agriculture, Forestry, Fishing and Hunting*						
Average obs	2,494,551	16,975	1,627,307	258,873	218	309,331
Percent	1.52	0.33	1.60	2.29	0.25	2.20
21 *Mining, Quarrying, and Oil and Gas Extraction*						
Average obs	811,883	21	565,338	12,832		45,202
Percent	0.50	0.00	0.55	0.11		0.32
22 *Utilities*						
Average obs	1,376,672	54	880,748	45,739	2	15,133
Percent	0.84	0.00	0.86	0.41	0.00	0.11
23 *Construction*						
Average obs	11,570,959	74,571	7,542,626	1,738,690	3,345	1,550,910
Percent	7.06	1.45	7.40	15.41	3.89	11.05

	(1) ASEC Full	(2) HB Full	(3) ASEC HB States	(4) ASEC Sample	(5) HB Sample	(6) QWI Sample
31–33 *Manufacturing*						
Average obs	16,094,836	36,759	9,863,228	323,252	1,137	684,610
Percent	9.82	0.71	9.67	2.86	1.32	4.88
42 *Wholesale Trade*						
Average obs	3,542,738	139	2,255,483	67,278		643,128
Percent	2.16	0.00	2.21	0.60		4.58
44–45 *Retail Trade*						
Average obs	17,088,628	697,119	10,869,406	1,211,602	14,354	1,432,060
Percent	10.43	13.53	10.66	10.74	16.68	10.20
48–49 *Transportation and Warehousing*						
Average obs	7,898,989	53,642	5,011,724	553,461	1,473	364,792
Percent	4.82	1.04	4.92	4.90	1.71	2.60
51 *Information*						
Average obs	2,981,793	22,408	1,819,702	90,754	249	162,600
Percent	1.82	0.43	1.78	0.80	0.29	1.16
52 *Finance and Insurance*						
Average obs	7,756,432	9,152	4,427,566	155,808	286	414,341
Percent	4.73	0.18	4.34	1.38	0.33	2.95
53 *Real Estate and Rental and Leasing*						
Average obs	3,345,098	16,122	2,187,264	166,022	931	444,381
Percent	2.04	0.31	2.15	1.47	1.08	3.17
54 *Professional, Scientific, and Technical Services*						
Average obs	13,114,794	113,104	8,199,848	674,572	3,770	1,486,339
Percent	8.00	2.19	8.04	5.98	4.38	10.59
55 *Management of Companies and Enterprises*						
Average obs	149,666	68,697	102,192		2,351	36,842
Percent	0.09	1.33	0.10		2.73	0.26
56 *Administrative and Support and Waste Management and Remediation Services*						
Average obs	7,060,830	52,337	4,704,635	782,275	2,317	772,320
Percent	4.31	1.02	4.61	6.93	2.69	5.50

	(1) ASEC Full	(2) HB Full	(3) ASEC HB States	(4) ASEC Sample	(5) HB Sample	(6) QWI Sample
61 *Educational Services*						
Average obs	15,165,151	77,058	8,954,306	469,870	1,695	216,475
Percent	9.25	1.50	8.78	4.16	1.97	1.54
62 *Health Care and Social Assistance*						
Average obs	22,289,792	243,838	13,349,828	1,630,383	9,837	2,271,235
Percent	13.60	4.73	13.09	14.45	11.43	16.18
71 *Arts, Entertainment, and Recreation*						
Average obs	3,767,820	194,149	2,311,177	355,276	2,953	292,277
Percent	2.30	3.77	2.27	3.15	3.43	2.08
72 *Accommodation and Food Services*						
Average obs	11,943,838	3,209,476	7,647,894	1,820,426	34,866	1,648,446
Percent	7.29	62.28	7.50	16.13	40.52	11.74
81 *Other Services (except Public Administration)*						
Average obs	7,839,014	263,762	4,978,586	801,013	6,096	1,249,554
Percent	4.78	5.12	4.88	7.10	7.09	8.90
92 *Public Administration*						
Average obs	7,600,328	1,947	4,648,719	126,967	161	0
Percent	4.64	0.04	4.56	1.13	0.19	0.00
76 *Misc. Repair*						
Average obs		2,233				
Percent		0.04				
Total						
Average obs	163,893,812	5,153,563	101,947,572	11,285,090	86,041	14,039,978
Percent	100.00	100.00	100.00	100.00	100.00	100.00

Note: ASEC and HB Full data include 2019 and 2020. QWI data is 2019 only. Column (3) ASEC is restricted to the 21 HB states. Column (4) ASEC sample is restricted to hourly workers, not self-employed, in small businesses ($<$ 25 employees) corresponding to HB NAICS codes in HB states. Column (5) HB sample is restricted to individuals eligible for full UI benefits (defined as meeting state specific earning requirements in previous quarters) with balanced number of week spells before and after FPUC. Column (6) QWI is avg. beginning of quarter employment in privately owned small firms ($<$ 20 employees) restricted to HB states.

C FPUC

Federal Pandemic Unemployment Compensation (FPUC), the weekly $600 supplement to unemployment benefits, was introduced by the CARES act enacted on March 27, 2020, and ended on July 31, 2020.[50] No FPUC benefits were payable between July 31, 2020 and December 26, 2020. FPUC was re-established by the Continued Assistance Act as a $300 per week supplement to unemployment benefits from December 26, 2020 to March 14, 2021.[51] American Rescue Plan Act extended FPUC through September 6, 2021.[52]

Any individual eligible to receive at least $1 of state unemployment benefits is also eligible to receive federally-funded FPUC for that week. Individuals who are working part-time and who fulfill state eligibility requirements for partial UI benefits are also eligible to receive FPUC payments.[53]

FPUC payments are federally funded; however, states can opt out of participating in the program. As of date, 7 of the 21 study states are planning to terminate some or all federally funded pandemic unemployment compensation programs early, citing labor supply shortages. FPUC will terminate on June 12, 2021 in Mississippi and Missouri; on June 19, 2021 in Alabama; on June 26, 2021 in Georgia; on June 30, 2021 in South Carolina; on July 3, 2021 in Tennessee; and on July 10, 2021 in Arizona.[54]

During the gap in FPUC payments, from August 1, 2020, Lost Wages Assistance (LWA) program was funded through Federal Emergency Management Agency (FEMA). States had the option of choosing between two weekly benefits amounts, $300 or $400, with different cost-sharing requirements. The $400 weekly benefit required the state to contribute $100 (25% of the benefit). The $300 weekly benefit was funded entirely by FEMA and states would satisfy the 25% match, without additional state pay-out, if the state funding for regular state UI benefits at the aggregate level amounted to at least 25% of total LWA benefits paid.[55] All 21 study states were approved for LWA, but only West Virginia picked the $400 weekly benefit option.[56] Individuals receiving at least $100 of weekly unemployment benefits were eligible for LWA – a stricter eligibility requirement than FPUC's requirement that an individual be eligible to receive at least $1 in weekly

[50] U.S. Department of Labor news release dated April 4, 2020, `www.dol.gov/newsroom/releases/eta/eta20200404`.

[51] U.S. Department of Labor news release dated January 5, 2021, `www.dol.gov/newsroom/releases/eta/eta20210105`. U.S. Department of Labor news release dated December 30, 2020, `https://www.dol.gov/newsroom/releases/eta/eta20201230-1`.

[52] U.S. Department of Labor news release dated March 16, 2021, `www.dol.gov/newsroom/releases/eta/eta20210316`.

[53] Attachment to Unemployment Insurance Program Letter No.15–20, Change 1, U.S. Department of Labor, dated May 9, 2020.

[54] The governor of Mississippi announced the termination of the programs over social media. Office of Governor Michael Parson (Missouri) press release dated May 11, 2021, `https://governor.mo.gov/press-releases` The Office of Alabama Governor press release dated May 10, 2021, `https://governor.alabama.gov`. Georgia Department of Labor press release dated May 13, 2021, `https://dol.georgia.gov` The Office of the Governor news release dated May 11, 2021, `www.tn.gov/governor/news` The Office of Governor Doug Ducey news release dated May 13, 2021, `https://azgovernor.gov/governor`.

[55] U.S. Department of Labor news release dated August 12, 2020, `www.dol.gov/newsroom/releases/eta/eta20200812-0`. Lost Wages Supplemental Payment Assistance Guidelines, `www.fema.gov`.

[56] Lost Wages Assistance Approved States, `www.fema.gov` The Office of the Governor Jim Justice (West Virginia) press release dated September 9, 2020, `https://governor.wv.gov`.

unemployment benefits.[57]

Participating states provided LWA to eligible individuals retroactively, beginning with the week of unemployment ending on August 1, 2020. Due to the fund's early depletion, benefits were paid for at most 6 weeks, until the week ending September 5, 2020.[58] All 21 study states except Florida received 6 weeks of funding. Florida was approved for 4 weeks, until the week ending August 22, 2020.[59]

FPUC and LWA together supplemented weekly unemployment benefits in the following periods depending on eligibility: \$600 (FPUC) from March 28, 2020 through July 31, 2020; \$300 (LWA) or \$400 (LWA, West Virginia) from August 1, 2020 through week ending September 5, 2020 (week ending August 22, 2020 in Florida); gap between September 5, 2020 and December 26, 2020; and \$300 (FPUC) from December 26, 2020 through September 6, 2021, with some states ending the program early.[60]

D Cobb-Douglas

Consider a case where utility is non-separable in health and consumption and take the cobb-douglas case with $g(m,h) = m^{\alpha}h^{1-\alpha}$. The FOC becomes:

$$1 - t - \Delta t = (1-r)\alpha(\frac{h}{m})^{(1-\alpha)} + r\alpha(\frac{h'}{m})^{(1-\alpha)} + \theta[m^{\alpha}h'^{1-\alpha} - m^{\alpha}h^{1-\alpha}]$$

From $U(c,l,h') = U(c-W,l,h)$ we can derive an expression for h':

$$m^{\alpha}h^{1-\alpha} = W(m) + m^{\alpha}h'^{1-\alpha}$$

using this in the FOC simplifies to

$$1 - t - \Delta t - (1+\alpha)\theta W(m) = \alpha(\frac{h}{m})^{(1-\alpha)}$$

Notice that this increases the implicit tax imposed by the health risk by factor α. This additional cost arises from the health effect on the marginal utility of leisure. A second change is that the utility cost of health now depends on the level of income m. Experiencing a health shock is more costly when an individual is working a lot. This increasing cost with m makes health risks operate like a non-linear progressive tax system.

[57] Although the size of the benefits are different for eligibility, the same programs qualify for both FPUC and LWA: regular unemployment compensation; Pandemic Emergency Unemployment Compensation (PEUC); Pandemic Unemployment Assistance (PUA); Extended Benefits (EB); Short-Time Compensation (STC); Trade Readjustment Allowances (TRA); Disaster Unemployment Assistance (DUA); and Self-Employment Assistance (SEA) program. U.S. Department of Labor news release dated April 4, 2020, `www.dol.gov/newsroom/releases/eta/eta20200404`. Lost Wages Supplemental Payment Assistance Guidelines, `www.fema.gov`.

[58] See, for example, Lost Wages Assistance, NC Department of Commerce, `https://des.nc.gov`.

[59] Florida Department of Economic Opportunity press release dated Sep 16, 2020, `www.floridajobs.org`.

[60] Unemployment Insurance Program Letter No. 14–21, U.S. Department of Labor, dated March 15, 2021.

D.0.1 Cobb-Douglas Case Without Uncertainty

Without uncertainty, the health cost is a simple function of the time spent at work. An hour of work $(1-l)$ has the health cost κ and $h = \kappa(1-l) = \kappa\frac{m}{a}$.

Denote the substitution elasticity between m and the composite good by e. In the Cobb-Douglas case:

$$g(\frac{m}{a}, h) = \frac{a}{1+1/e}(\frac{m}{a}^{1-\alpha}h^{\alpha})^{(1+1/e)}$$

If $\alpha = 0$ this model becomes the canonical 2 good leisure-labor economy. From the FOC of the utility maximization, the optimal m^o follows:

$$m^o = \theta(1 - T'(m^o))^e$$

with $\theta = a\kappa^{-\alpha(1+e)}$. The canonical bunching approach for notches identifies e from the marginal buncher. The marginal buncher is the person who is just indifferent between the notch point and a higher income level. This persons' IC is thus tangent to the BC and also touches the notch point. Call the utility at the notch point U^* and the utility at the tangent point U^o, for the marginal buncher $U^* = U^o$. The notch utility U^* for the marginal buncher $\hat{a}$ is:

$$U^* = (1-t)m^* - \frac{\hat{a}}{1+1/e}(\frac{m^*\kappa^{\alpha}}{\hat{a}})^{(1+1/e)}$$

using the FOC result $m^o = \theta(1-T'(m^o))^e$ we can write U^o as:

$$U^o = (1-t-\Delta t)\theta(1-t-\Delta t)^e - \frac{\hat{a}}{1+1/e}(\frac{\theta(1-t-\Delta t)^e\kappa^{\alpha}}{\hat{a}})^{(1+1/e)}$$

$$U^o = \frac{1}{1+e}\hat{a}(1-t-\Delta t)^{1+e}\kappa^{-\alpha(1+e)}$$

We combine the two utility expression and use the relation $\hat{a} = \tilde{m^o}\kappa^{\alpha(1+e)}/(1-t)^e$, to write down an implicit solution for e in terms of κ, α, m and t:

D.1 Income Effects

The canonical bunching approach uses quasi-linear utilities and thus assumes that there are no income effects. In many contexts where notches are small, the absence of income effects is plausible. Recent work, however, stresses that small notches may not be salient (Chetty, Friedman, and Saez, 2013). Moving to larger notches is thus attractive but leads to the added complication that such notches produce income effects. Structural estimates have previously used utility functions with income effects (Blundell, MaCurdy, and Meghir, 2007). Below we aim to cover a middle ground between the functional form flexibility of structural work and the quasi-experimental approach to identification of the bunching literature. We will show that excess mass does not only appear at m^* but also appears at lower income ranges with income effects.

D.1.1 Estimating Labor Supply Responses

Consider a more general labor supply function that allows for income effects:

$$\tilde{m^o} = \tilde{a} + e\tilde{w} - \gamma\tilde{y} \tag{6}$$

$\tilde{x}$ indicates log values and $\gamma\tilde{y}$ captures the income effect. When $\gamma = 0$ this equation collapses to the canonical quasi-linear utility case without income effects.

The introduction of a lump sum benefit Δt reduces labor supply if $\gamma < 0$. This effect changes the impact of the non-linear benefit schedule studied above. For a worker just to the right of the eligibility notch at $m^* + \epsilon$, labor supply falls to $m^* + \epsilon - \gamma\Delta$ which is to the left of m^* if ϵ is small. The labor supply response thus creates excess mass left of m^* and the excess mass at the notch point therefore does not fully capture the labor supply response. A special scenario where all excess mass occurs at the kink point is the case without income effects ($\gamma = 0$). In such a scenario, the worker at $m * + \epsilon$ would move to m^* and since the income effect is smaller for all workers with higher initial incomes, all bunchers will move to m^* and all excess mass occurs in a single point at m^*.[61] With income effects E does not appear at one specific point of the distribution but spreads out across a broader range of incomes, which creates additional identification challenges. We will return below to the question of how to identify excess mass over a wider income range.

The excess mass E is closely linked to the labor supply response of the marginal buncher. Individuals with pre-period income between m^* and the income of the marginal buncher $m^* + \Delta m$ make up the excess mass and E is thus given by:

$$E = \int_{m^*}^{m^*+\Delta m} h_0 dm$$

$$\Delta m = E/h_0 \tag{7}$$

where h_0 is the pre-notch wage distribution between m^* and $m^* + \Delta m$. To keep notation simple, we assume that the pre-period wage distribution is constant over this segment.[62]

To compute Δm we need to estimate h_0 and E. We can directly compute h_0 from the data if data on the pre-notch distribution is available. Such a pre-period distribution provides a valid counterfactual under a parallel trend assumption, similar to the assumption required in a difference in differences regression.[63]

A second step is to estimate E, the extra mass generated by bunching individuals. E is the difference between the observed post-notch income distribution (h_1) and the distribution of non-bunchers (h_0'):

$$h_1 = E + h_0', \tag{8}$$

[61]Note that this is a kink point and hence $\tilde{m^o}$ does not hold

[62]This assumption simplifies notation but is not required and richer baseline distributions can be included in the estimation.

[63]Without data on the pre-period, h_0 can still be estimated with "untreated" income ranges away from the notch point. This requires to estimate h_0 in such untreated income ranges and then extrapolate to incomes in the treatment range. The researchers will need to make an assumption about which income ranges are untreated, and this requirement of an ad-hoc assumption has been controversial (Blomquist et al., 2021). The presence of income effects worsens the problem. Bunching is more spread out with income effects and less sharp at the cut-off, making it harder to define untreated income bins.

In practice, h_0' is not directly observed and needs to be estimated. Typically $h_0' \neq h_0$ and the pre-distribution does not provide a valid counterfactual. To see why, consider workers at m^* in the pre-period, they are to the left of the notch and thus part of the non-bunchers. However, the notch still affects their behavior, with the introduction of benefit labor supply falls to $m^* - \gamma\Delta$. As a result, there is no mass at m^* and $h_0'(m^*) = 0 \neq h_0(m^*)$. Using h_0 as counterfactual will bias the results, $h_0'(m^*) = 0$ implies that *all* individuals at $m = m^*$ are bunchers and the spike in density above neighboring cells ($\hat{E} = h_1(m^*) - \hat{h_0}(m^*) < E$) underestimates the true extend of bunching. Much of the debate about income effects focuses on the difference in compensated and uncompensated labor supply elasticities. It is important to note that the impact is more severe in the context of bunching estimates. Here, income effects not only affect the interpretation of the elasticity as (un)compensated but additionally bias the labor supply response estimate itself.

Unbiased estimates can be obtained without income effects. This is the canonical bunching assumption with $\gamma = 0$. Here $h_0 = h_0'$ as the labor supply of non-bunchers is unaffected by the introduction of the notch and as a result the spike in mass relative to neighboring regions provides an unbiased estimate ($\hat{E} = h_1(m^*) - \hat{h_0}(m^*) = E$). Assuming income effects away is thus an important underlying assumption of the canonical bunching approach.

For the more general case, valid estimates can be obtained with a difference in difference analysis. A first advantage of the difference in difference approach is that it can detect any deviations from the pre-notch distribution, not just spikes in one specific location. As we saw above, this is important with income effects. Additionally, the difference in difference approach can overcome the identification challenge created by $h_0' \neq h_0$. When leisure is a normal good, the introduction of benefits reduces labor supply among the non-bunchers. Note, that while the local distribution of m is changed, the total mass of non-bunchers below m^* is unaffected by the notch:

$$\int_0^{m^*} h_0' = \int_0^{m^*} h_0 \equiv \pi$$

Using this result in 8, we can show that the notch generates total excess mass:

$$\int_0^{m^*} E = \int_0^{m^*} h_1 - \int_0^{m^*} h_0$$

which is the difference in the total density below the notch before and after the notch-reform. $\int_0^{m^*} E$ can be estimated in a difference in difference regression that compares the density below m^* before and after the introduction of the notch. In difference in differences notation:

$$Pr(I = m)_{t,m} = \phi \cdot 1[t > t^*] + \pi \cdot 1[m < m^*] + \bar{E} \cdot 1[t > t^*] \cdot 1[m < m^*] + \varepsilon_{t,m}$$

where t^* is the time of the reform, π is captured by the coefficient on the dummy $1[m < m^*]$. The coefficient $\bar{E}$ captures the average rise in density below m^*. Substituting this estimate into 7 yields the labor supply response of interest Δm.

The setting also yields an identification check in the spirit of a parallel trend check. This test is based on the distribution of the excess mass relative to the notch point. If the notch generates the excess mass, excess mass should peak near the notch and decline as we move away from the notch. To test this, we estimate a specification similar to a dynamic DiD, and let the E coefficient vary across income ranges:

$$Pr(I = m)_{t,m} = \phi \cdot 1[t > t^*] + \pi \cdot 1[m < m^*] + E_m \cdot 1[t > t^*] \cdot 1[m < m^*] + \varepsilon_{t,m}$$

Plotting E_m provides a visual check on the assumption that the notch generates excess mass. The excess mass should peak at m^*, and it's mirror image, missing mass, should peak to the right of m^*. Finally, for m further from m^*, the effects should diminish.

Similar "difference in bunching" approaches have been used in the literature (Brown, 2013; Best et al., 2015), typically as a check on the identification assumption of canonical bunching estimators. In the set-up above we explicitly leverage the additional degrees of freedom to broaden the applicability of bunching methods to preferences with income effects.

These issue can be addressed with a difference in differences set-up. For such an approach both a period before and after the introduction of the notch needs to be observed. Comparing the income distribution below m^* before and after the introduction of the budget notch identifies E.

D.1.2 Compensated Elasticity

The previous section's reduced form labor supply response can be used to estimate structural preference parameters that have validity beyond the specific context. The canonical reduced form approach calculates an upper bound of the compensated labor supply elasticity as $e_c < \frac{(1-\Delta m)^2}{1-\Delta t}$. With income effects the formula yields an upper bound for the uncompensated labor supply elasticity (e_u).

To make further progress, we need to specify a functional form for preferences. The standard approach is to assume a quasi-linear utility function. Such preferences do not have income effects and to allow for a more general case we will thus use a preference structure that includes the possibility of income effects. Preferences can be specified either by assuming a functional form of the utility function, the indirect utility function or the labor supply function.[64] A large empirical literature estimates a linear labor supply function as in 6 (Hausman, 1985; Blomquist, 1983) and we will follow this literature and use the same labor supply function. Such preferences allow for income effects. Specifically, the substitution and income effects are respectively captured by e and γ. Notice that this assumption nests the quasi-linear case with $\gamma = 0$.

The estimation largely follows the same procedure as the canonical bunching approach, however there is one additional parameter, the income effect γ. To solve for this additional parameter requires one additional moment condition and we can use the dispersion of excess mass for this purpose. Without income effects all excess mass arises at m^*, while the excess mass is more spread out the bigger the income effects.

To derive a solution for γ we leverage the location of bunching. Note that all bunchers below m^* are at an interior solution. There will be one bunching person for whom m^* is an interior solution, call this person the marginal buncher from the left. Before the notch the income of this person was $h_0 = m^* + p$. And using those two labor supply decisions in 6, we can show that:

$$m^* + p - \tilde{a} - e\tilde{w} + \gamma\tilde{y} = m^* - \tilde{a} - e\tilde{w} + \gamma(\tilde{y} + \Delta T)$$

[64]The can be imposed on any any of the three functions. Roy's identity allows to derive direct and indirect utility functions from labor supply functions (up to a constant, which is meaningless for ordinal utility) and vice-versa.

$$\gamma = p/\Delta T$$

We can thus solve for γ by deriving p. Notice that everyone with $h_0 \leq m^* + p$ is an interior buncher and the total mass of interior bunchers is thus:

$$I = \int_{m^*}^{m^*+p} h_0$$

The excess mass below the notch point (I) thus pins down p, e.g. with h_0 constant $p = I/h_0$. And using p, we can solve for $\gamma = \frac{I}{h_0 \Delta T}$. If all excess mass arises at the notch point then $I = 0$ and consequently $\gamma = 0$ and the analysis collapses to the quasi-linear case. This approach can thus be used to check the validity of canonical bunching estimates. But more powerfully, it can be used to identify labor supply responses from large and salient notches in budget constraints.

E Border Design

In this section we narrow our sample to counties along state boundaries, and thus with similar characteristics but facing different UI eligibility rules. The border counties are shown in Figure A4. Our sample states comprise 19 border stretches, and our sample includes 16 of those, excluding places where our sample has no observations in border counties (3 border stretches).

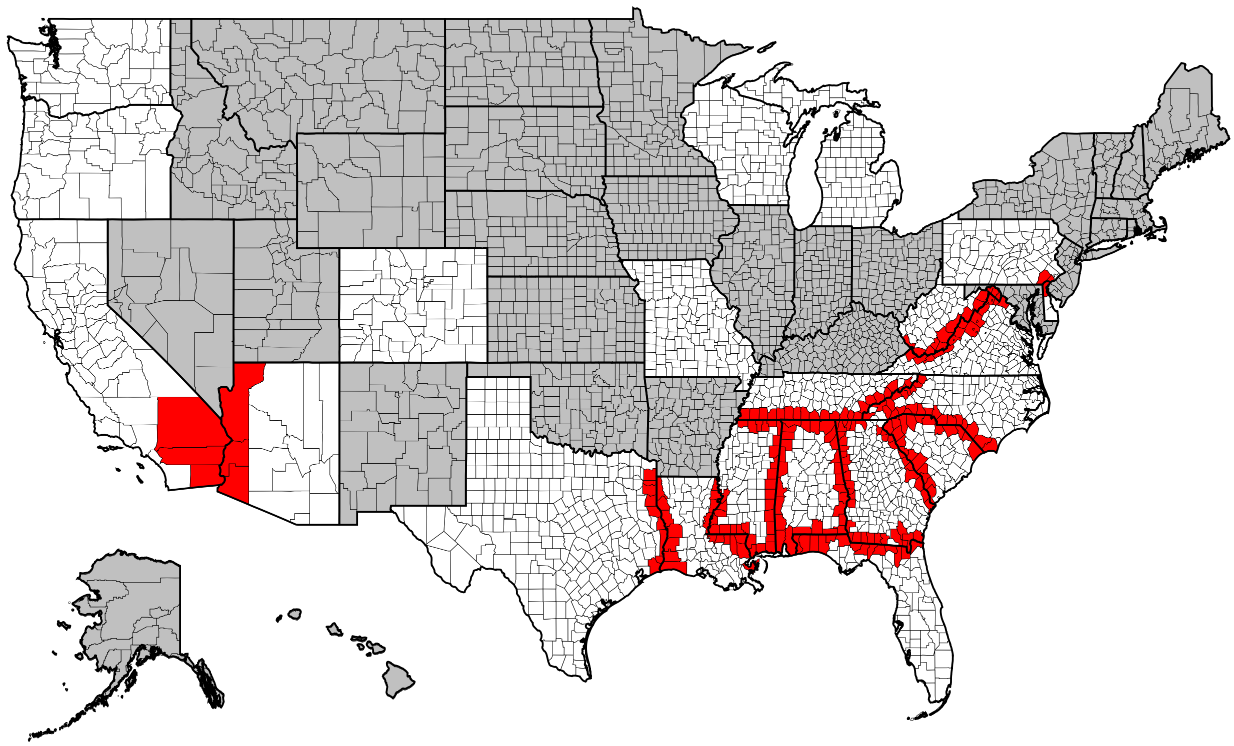
In the first step, we repeat the baseline analysis on the sample of border counties and find very similar effects to the baseline (Column 1 of Table A3). Next, we exploit the idea that neighboring counties experience similar demand shocks and allow all fixed effects to be specific to each border stretch. In practice, this implies that each border stretch is it's own DiD experiment and we stack the 14 border DiDs into a single regression. Since our power in these regressions is limited, we interact local time effects with a continuous measure of income, instead of letting time effects vary non-parametrically by income bins. The results of these regressions are again close to our baseline estimates (column 2).

Table A3: Excess Mass around UI Eligibility Threshold - Border Counties Sample

	(1)	(2)
Excess Mass (ptp)	0.823	0.945
	(0.157)	(0.127)
Interact income x		
time FE with		border
Observations	531,496	531,496

Note: The Table reports results from equation 4. The border sample is restricted to counties at state borders shown in Figure A4. Source: Homebase.

Figure A4: Border Counties in Sample



Note: The Figure shows counties along state boundaries that are included in our border sample.

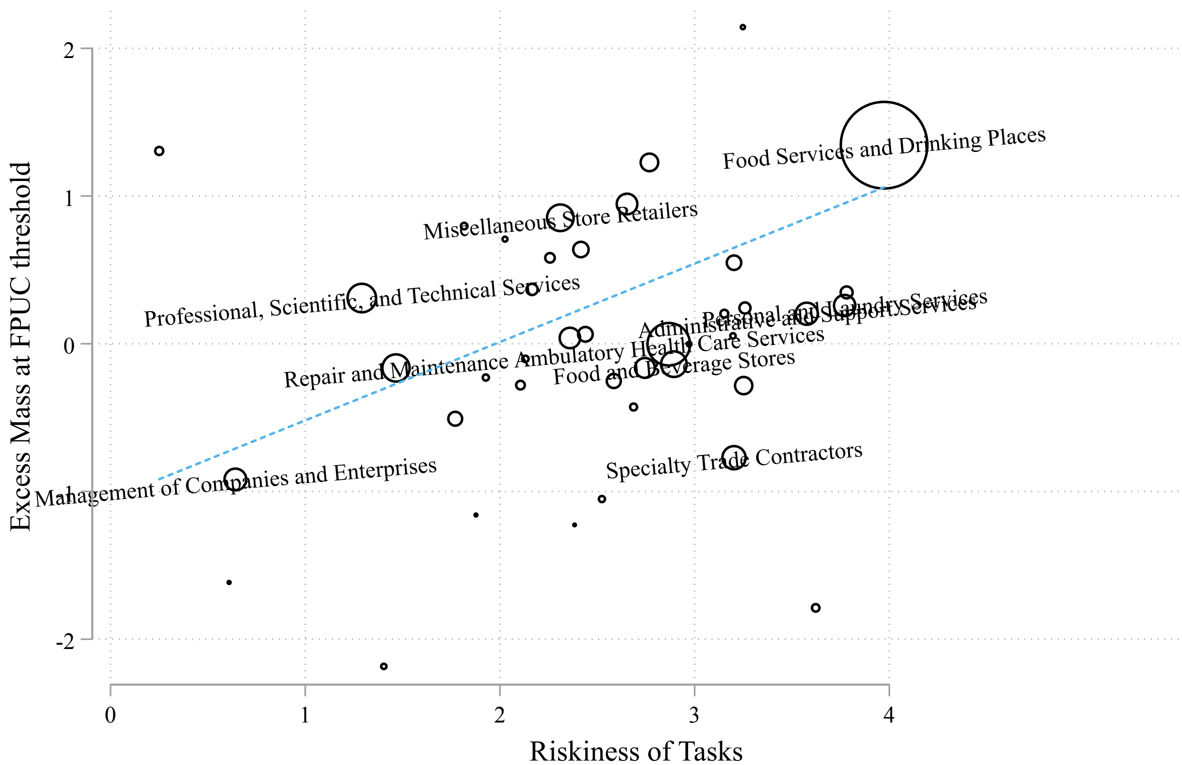
F Alternative Measures of Covid-19 Exposure

In this section we estimate the labor supply response to the increase in workplace risk using two alternative measures of Covid-19 exposure: the simple cross-industry task variation (i.e. the I_i component of $\theta_{i,c,t}$ from equation 5) and local Covid-19 outbreaks *within* the county $F_{c,t}$, measured as by the number of deaths per 1 million people.

Figure A5 plots how industry risks I_i affect labor supply behavior. An increase in pre-determined industry risk results in a significantly greater amount of excess mass around the FPUC threshold and hence a reduction in labor supply. These results are highly significant, with excess mass increasing 0.5 percentage point for a standard deviation increase in risk. Workers thus shy away from high risk workplaces, in line with negative compensating differentials. The strong explanatory power of the regression shows that workplace safety is an important driver of labor supply behavior. The R^2 of the regression is 0.44; workplace risks thus explain almost half of the variation in labor supply behavior across industries.

In Figure A6 we focus instead on the labor supply response to county/week variation in Covid-19 death risk. We split $F_{c,t}$ into five categories and estimate the responses separately for those five risk levels. The excess/missing mass in red –replicated identical in all four panels– represents the behavioral response to FPUC in counties with zero recorded new deaths. In the top left panel of Figure A6, the blue area represents the "excess response" to FPUC in counties with a relatively low observed Covid-19 risk (between 0 and 15 weekly new deaths per million people). Despite the relatively low risk, it is visible that workers in these counties are responding more vigorously to the FPUC incentives relative to counties with zero risk. In these counties, workers appear to choose to move down the earning distribution more than in the zero-risk ones. As before, we are controlling for demand shocks with income range specific time effects. The remaining three panels show how the "excess response" increases with death risk. The excess mass of workers shifting to the left of the state-specific notches is particularly pronounced for very high-risk counties (more than 45 weekly new deaths per million people)

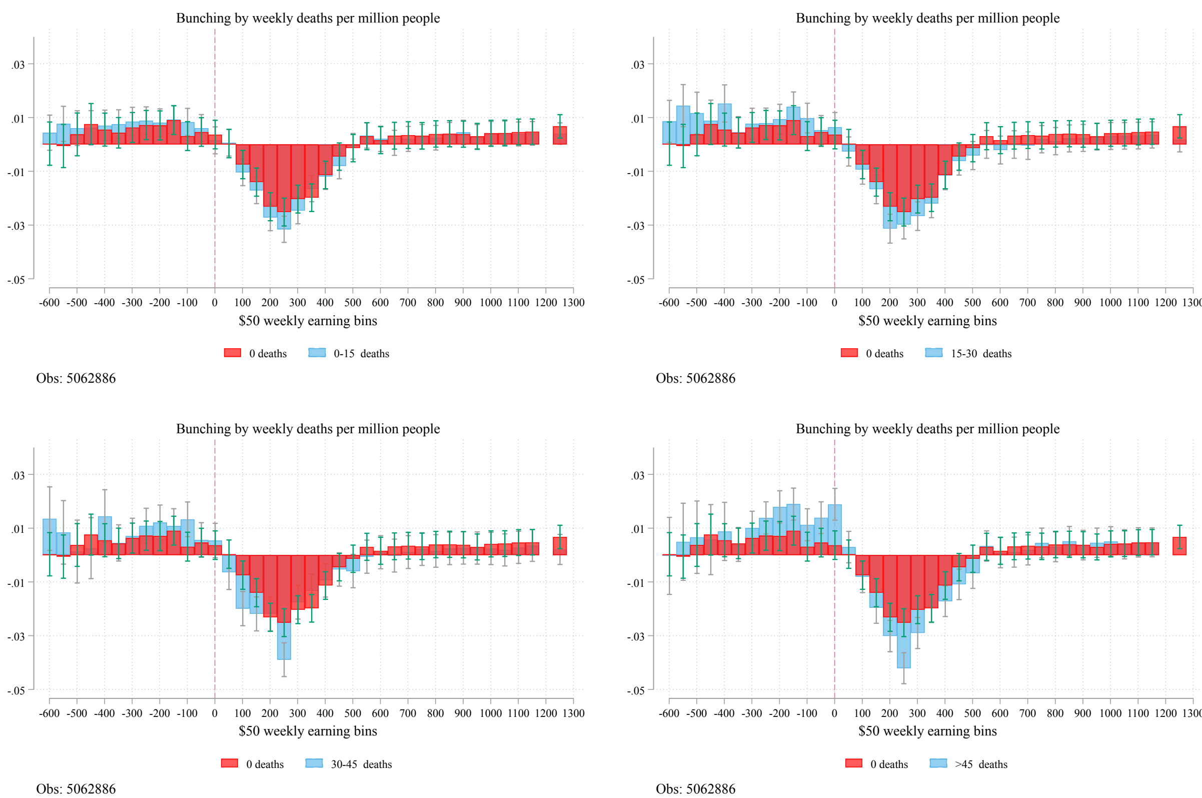
Figure A5: Effect of Workplace Safety on Labor Supply – Task Risk Proxy



Note: The Figure shows the amount of excess mass at the FPUC threshold for 3-digit NAICS industries. The riskiness of tasks is the average risk of Covid-19 infections among tasks performed in the industry. The task risk data comes from Basso et al. (2021) and risk scores are standardized to have a standard deviation of 1. The y-axis shows the amount of excess mass generated by the FPUC eligibility threshold and is estimated in equation 3. The omitted industry is industry 111 (crop production). Industry titles are shown for the ten largest industries and for display purposes we only show industries with at least 1,000 observations. The size of the markers corresponds to the cell-size and regressions weight by cell-size. The fitted line has a slope coefficient of 0.5 and an $R^2 = 0.44$ Source: Homebase.

We next use the magnified "excess response" to compute the implied WTP for workplace safety. The WTP –computed using equation (1) presented in Section 3– increases in a rather linear pattern and varies between a bit more than 10% of disposable income for counties with relatively low risk (top left panel of Figure A6) to 50% of disposable income in very high-risk counties.

Figure A6: Excess and Missing Mass around the Partial UI Notch – Fatality Rate in County



Note: The Figure shows $\delta_{k,\theta}$ coefficients from equation 4. Results for 4 different Covid-19 risk levels (θ) are plotted in each panel in blue. Covid-19 risk is measured as deaths per million in the week in the local area. The red bars are the benchmark response in areas with 0 Covid-19 deaths. The sample covers hourly workers with sufficient past earnings to qualify for MWB payments in their home state. Source: Homebase.

G Robustness Checks

As additional robustness test, we investigate potential biases from demand shocks and explicitly control for proxies of such shocks (Table A4). We include controls from Chetty et al. (2020a), which cover weekly state-industry measures of employment, revenues of small businesses and business closures. In column 6 we also control for school closures, a factor that might confound labor supply responses.[65] Estimates are robust to the inclusion of each of these controls and all these controls simultaneously (column 6), confirming the efficacy of our threshold design in isolating labor supply responses.

Table A4: Robustness to Labor Demand Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Additional Excess Mass			
Workplace Risk	0.353	0.347	0.348	0.347	0.346	0.354	0.348
(std. dev.)	(0.0565)	(0.0561)	(0.0562)	(0.0562)	(0.0561)	(0.0566)	(0.0563)
Controls		# Employees	Small Business Revenues	Change in # merchants	Revenues X Merchants	Share of in-class instruction	All

Note: Columns (2) through (7) supplement the main specification of Panel B of Table 2 (also presented in column (1)) by controlling for demand shock proxies, interacted with a dummy for the Covid-19 period and a continuous income variable. Column (2) controls for the number of active employees from Paychex, Intuit, Earnin and Kronos, varying at state-week-industry level. Column (3) controls for the percent change in net revenue for small businesses from Womply, varying at state-week-industry level. Column (4) controls for the percent change in number of small businesses open from Womply, varying at state-week-industry level. Column (5) interacts the percent change in net revenue with percent change in the number of small businesses from Womply. Employment, revenue and merchants data are downloaded from Opportunity Insights Economic Tracker. Column (6) controls for the share of in class instruction from Parolin and Lee (2021), varying at county-month level. The share of in class instruction is defined as the complement of the share of all schools in an area with at least 50% year-over-year decline in visitors, consistent with the Parolin and Lee definition. Column (7) controls for all demand shock proxies together. Sources: Chetty et al. (2020a); Chetty et al. (2020b); Parolin and Lee (2021a); Parolin and Lee (2021b).

[65]Employment and Small Businesses daily data are obtained from Chetty et al. (2020a), while the share of in class instruction is obtained from Parolin and Lee (2021a)