

Online Appendix for the manuscript

“Willingness to Pay for Workplace Amenities”

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A Online Appendix Tables and Figures

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Figure A1: Scheduling App Screenshot

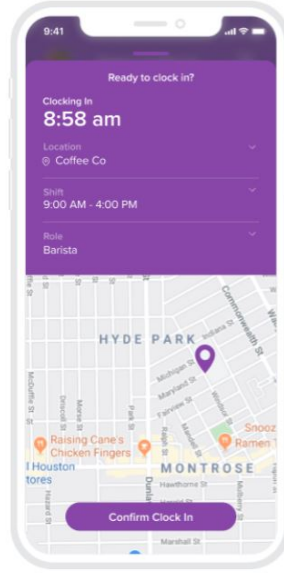
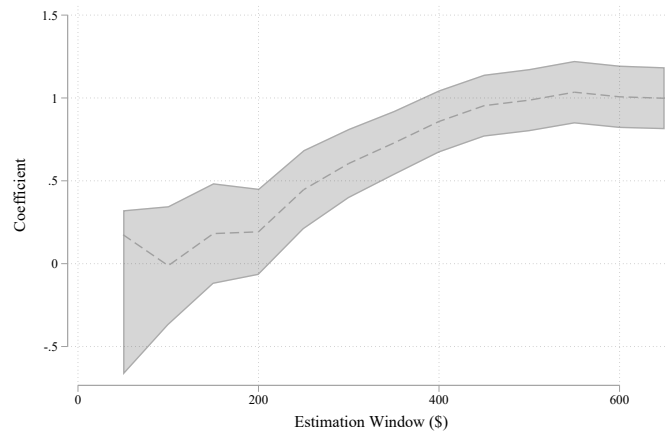


Figure A2: Effect of FPUC with Alternative Treatment Windows



Note: This figure shows results for equation (10) with alternative treatment windows T_k . The horizontal axis refers to the width of T_k to the left and right of the threshold.

B Homebase Data Benchmarking

We compare the Homebase data and our analysis sample to the characteristics of the labor force from the Annual Social and Economic (ASEC) supplement to the Current Population Survey (CPS) and the Quarterly Workforce Indicators (QWI). Table A1 presents summary statistics for wages, weekly earnings, and hours worked and Table A2 lists the distribution of observations by 2-digit NAICS sectors in these data.

Homebase provides 6 digit NAICS codes but ASEC does not provide an industry classification that uses NAICS. Therefore, to allow for comparability of ASEC to the Homebase sample, the industry classification in ASEC is first crosswalked to NAICS using the crosswalk provided by IPUMS.¹ 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 being 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).

¹See "IND AND INDNAICS: CODES FOR INDUSTRY (IND) AND NAICS INDUSTRY (IND-NAICS) 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 (10.84)	12.26 (4.837)	18.46 (10.66)	16.69 (9.085)	18.35 (8.146)	
Weekly earnings	1016.7 (724.4)	377.0 (243.1)	999.6 (716.1)	635.2 (435.5)	660.1 (345.1)	805.5 (328.4)
Hours usually worked per week at all jobs	39.25 (11.30)		39.32 (11.11)	35.87 (11.07)		
Hours usually worked per week at main job	38.55 (10.84)	29.93 (13.24)	38.66 (10.69)	35.21 (10.68)	36.49 (12.78)	
Hours worked last week	38.45 (12.80)		38.49 (12.63)	34.89 (12.11)		

Note: Mean coefficients and standard errors are in parentheses. ASEC and HB Full data include 2019 and 2020. QWI data is from 2019 only. Column (3) ASEC is restricted to the 21 HB states. Column (4) ASEC sample is restricted to hourly workers, who are not self-employed, working in small businesses (< 25 employees) in a HB state and industry. Column (5) HB sample is restricted to individuals eligible for full UI benefits (defined as meeting state-specific earnings requirements in previous quarters) with a balanced number of week spells before and after the onset of the COVID-19 pandemic. Column (6) QWI sample is restricted to privately owned small firms (< 20 employees) in HB states. Weekly earnings are calculated from the average monthly earnings (divided by 4.345) of the beginning-of-quarter employment. Source: Homebase, ASEC, QWI.

C Institutional Details

C.1 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, 2020.² 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, 2021.³ American Rescue Plan Act extended FPUC through September 6, 2021.⁴ Any individual eligible to receive at least \$1 of state unemployment benefits was also eligible to receive federally-funded FPUC for that week. Individuals who were

²U.S. Department of Labor news release dated April 4, 2020.

³U.S. Department of Labor news releases dated December 30, 2020, and January 5, 2021.

⁴U.S. Department of Labor news release dated March 16, 2021.

Table A2: Distribution of Observations by NAICS 2

	(1) ASEC Full %	(2) HB Full %	(3) ASEC HB States %	(4) ASEC Sample %	(5) HB Sample %	(6) QWI Sample %
11 Agriculture	1.52	0.28	1.60	2.42	0.30	2.20
21 Mining	0.50	0.00	0.55	0.59		0.32
22 Utilities	0.84	0.00	0.86	0.40	0.00	0.11
23 Construction	7.06	1.44	7.40	15.29	4.32	11.05
31–33 Manufacturing	9.82	0.71	9.67	2.84	1.40	4.88
42 Wholesale Trade	2.16	0.00	2.21	0.59		4.58
44–45 Retail Trade	10.43	13.42	10.66	10.65	16.06	10.20
48–49 Transportation	4.82	1.06	4.92	5.02	1.87	2.60
51 Information	1.82	0.40	1.78	0.80	0.22	1.16
52 Finance & Insurance	4.73	0.18	4.34	1.37	0.34	2.95
53 Real Estate	2.04	0.31	2.15	1.46	1.15	3.17
54 Professional Services	8.00	2.23	8.04	5.93	4.68	10.59
55 Management	0.09	1.32	0.10		3.14	0.26
56 Admin. & Support	4.31	1.00	4.61	6.88	2.79	5.50
61 Education Services	9.25	1.50	8.78	4.13	1.80	1.54
62 Health Care	13.60	4.84	13.09	14.34	13.10	16.18
71 Arts, Entertainment	2.30	3.77	2.27	3.12	3.58	2.08
72 Accommodation & Food	7.29	62.26	7.50	16.01	37.90	11.74
81 Other Services	4.78	5.19	4.88	7.04	7.13	8.90
92 Public Administration	4.64	0.04	4.56	1.12	0.21	0.00

Note: ASEC and HB Full data include 2019 and 2020. QWI data is from 2019 only. Column (3) ASEC is restricted to the 21 HB states. Column (4) ASEC sample is restricted to hourly workers, who are not self-employed, working in small businesses (< 25 employees) in a HB state and industry. Column (5) HB sample is restricted to individuals eligible for full UI benefits (defined as meeting state-specific earnings requirements in previous quarters) with a balanced number of week spells before and after the onset of COVID-19 pandemic. Column (6) QWI sample is restricted to privately owned small firms (< 20 employees) in HB states, and only beginning-of-quarter employment.

working part-time and fulfilled state eligibility requirements for partial UI benefits were also eligible to receive FPUC payments.⁵

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 benefit amounts, \$300 or \$400,

⁵Attachment to Unemployment Insurance Program Letter No.15–20, Change 1, U.S. Department of Labor, dated May 9, 2020.

with different cost-sharing requirements.⁶

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 from August 1, 2020, through the 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.⁷

C.2 Eligibility for Partial Unemployment Insurance

The \$600 FPUC benefit was received by all workers on Unemployment Insurance or Partial Unemployment Insurance (i.e. who reduced their hours worked or are working a limited amount of hours while on unemployment), hence by every worker with earnings below the threshold determining the access to Partial Unemployment Insurance. Between March and July of 2020, individuals crossing this earnings threshold exhausted all remaining UI benefits and forfeited the \$600 FPUC benefit. Crucially for identification, this threshold differs across the 21 US states. Table A3 shows the threshold for each state in column 5, as we calculated it based on State-specific UI eligibility rules reported by the Department of Labor (DOL) for the year 2020 in their document titled “The Comparison of State Unemployment Insurance Laws”.⁸ In most states, an individual is considered partially unemployed in some week if working less than full-time with earnings less than the weekly benefit amount or less than a percentage of, or less than a multiplier of the weekly benefit amount. Since we do not observe the actual UI benefits in our sample, we focus our analysis on workers who have an

⁶U.S. Department of Labor news release dated August 12, 2020, Lost Wages Supplemental Payment Assistance Guidelines.

⁷Unemployment Insurance Program Letter No. 14–21, U.S. Department of Labor, dated March 15, 2021.

⁸Available at <https://oui.doleta.gov/unemploy/comparison/2020-2029/comparison2020.asp>

earnings history that makes them eligible for maximum UI benefits. In columns 1 and 2 of Table A3 we thus report, from Table 3-5 of the DOL document, the maximum UI weekly benefit amount (WBA) allowed in each state. In three states, the maximum WBA is slightly higher for individuals with dependence. For these three states, we consider the higher maximum WBA as a reference for our calculations. In columns 3 and 4 we report, from Table 3-8 of the DOL document, the maximum amount of labor market earnings allowed to retain eligibility for partial UI benefits and the earnings to be disregarded when this maximum amount is calculated.⁹ In column 6 of Table A3 we report how we have processed the information provided by the DOL to calculate the Partial UI thresholds of column 5. In Michigan, Washington and Wisconsin, eligibility for partial UI benefits is also conditional on workers reducing hours below a certain amount of hours per week. Considering the sample of workers under analysis, in most cases reducing earnings to an amount below the earnings threshold also corresponds to meeting the hour condition. For instance, consider the case of the 32 maximum weekly hour threshold for Wisconsin: given an average hourly wage of \$18 and the \$500 earnings threshold, a worker would work 27 hours a week, well below the 32-hour condition. Therefore, at the cost of a potential small amount of measurement error, we focus only on the earnings threshold to determine FPUC eligibility also for these three states. During the first month of COVID-19 emergency, Georgia has temporarily increased the earnings amount disregarded for the calculation of the Partial UI threshold. We have considered this temporary change relative to the DOL document in our calculation.

⁹All states disregard some earnings as an incentive to take part-time or short-term work.

Table A3: State-specific eligibility rules for access to partial UI benefits

		(1)	(2)	(3)	(4)	(5)
State	Max WBA (\$)	Max WBA with dependence (\$)	Definition of Partial UI. Earnings less than:	Earnings Disregarded	Threshold (\$)	Calculation
Alabama	275		WBA	$\frac{1}{3}$ WBA	367	Max WBA + $\frac{1}{3}$ *Max WBA
Arizona	240		WBA	\$30	270	Max WBA + Earnings Disregarded
California	450		WBA	Greater of \$25 or $\frac{1}{4}$ of wages	600	Max WBA/0.75
Colorado	561	618	WBA	$\frac{1}{4}$ WBA	773	1.25*Max WBA with dependence
Delaware	400		WBA + greater of \$10 or $\frac{1}{2}$ WBA	Greater of \$10 or $\frac{1}{2}$ WBA	800	Max WBA + 2*0.5*Max WBA
Florida	275		WBA	8 x Federal hourly minimum wage	333	Max WBA + 8*7.25
Georgia	365		WBA	\$50	715	Max WBA + Earnings Disregarded + \$300
Louisiana	221	284	WBA	Lesser of $\frac{1}{2}$ WBA or \$50	334	1.5* Max WBA with dependence
Michigan	362		1.6 x WBA	For each \$1 earned, WBA is reduced by 50 cents (benefits and earnings cannot exceed 1.6 WBA)	434	0.6*Max WBA/0.5

State	Max WBA (\$)	Max WBA with dependence (\$)	Definition of Partial UI. Earnings less than:	Earnings Disregarded	Threshold (\$)	Calculation
Mississippi	235		WBA	\$40	275	Max WBA + Earnings Disregarded
Missouri	320		WBA + \$20 or 20%WBA, whichever is greater	\$20 or 20% WBA, whichever is greater	448	Max WBA + 0.2*Max WBA
North Carolina	350			20% WBA		
Oregon	648		WBA	Greater of \$120 or $\frac{1}{3}$ WBA	864	Max WBA + Max WBA/3
Pennsylvania	561	569	WBA + 40% WBA	Greater of \$21 or 30% WBA	967	1.4*Max WBA with dependence + 0.3*Max WBA with dependence
South Carolina	326		WBA	$\frac{1}{4}$ WBA	408	1.25*Max WBA
Tennessee	275		WBA	Greater of \$50 or $\frac{1}{4}$ WBA	344	Max WBA + Max WBA/4
Texas	521		WBA + greater of \$5 or $\frac{1}{4}$ WBA	Greater of \$5 or $\frac{1}{4}$ WBA	782	Max WBA + 2*Max WBA/4
Virginia	378		WBA	\$50	428	Max WBA + \$50
Washington	790		1.33 WBA + \$5	$\frac{1}{4}$ wages over \$5	1.414	(1.33*Max WBA + \$10)/0.75
West Virginia	424		WBA + \$61	\$60	545	Max WBA + \$60 + \$61

State	Max WBA (\$)	Max WBA with dependence (\$)	Definition of Partial UI. Earnings less than:	Earnings Dis-regarded	Thresh-old (\$)	Calculation
Wisconsin	370		500	\$30 plus 33% of wages in excess of \$30	500	No benefits are payable if weekly earnings exceed \$500.

D Model Extensions

D.1 WTP Approximation and Bounds

Here we show that the approximation in (8c) holds exactly in the case of kinks and provides a tight lower bound for notches.

First, consider the case of a regression kink design, where the marginal tax rate increases by Δt at m^* and will show that equation (8c) holds. Recall that the definition of labor supply elasticity is $e = \frac{m_L^o - m^*}{m^*} / \frac{\Delta \tilde{t}}{1 - \tilde{t}}$, where $\tilde{t}$ is the implicit tax rate $t + \theta W$. We derive an expression for W by evaluating the elasticity in two risk scenarios with $\theta_L = 0, \theta_H$. Assuming that risks are smooth at the threshold, we can use the ratio of the two elasticity expressions to obtain:

$$1 = \frac{m_L^o - m^*}{m_H^o - m^*} \frac{1 - t}{1 - t - \theta_H W} \quad (11)$$

Next, we can prove the claim by re-arranging this expression and using the definition of $WTP(r) = \frac{rW}{m^*(1-t)}$:

$$WTP(r) = \frac{m_H^o - m_L^o}{m_H^o - m^*} \quad (12)$$

Next consider the case of notches. Here the approximation in equation (8c) provides a lower bound estimate of the true WTP. To see this, recall that $WTP(r) = 1 - \frac{\frac{m_L^o}{m^*} \gamma_L - 1}{\frac{m_H^o}{m^*} \gamma_H - 1}$. The approximation result sets $\gamma_H = \gamma_L = 1$. The difference between such an approximation and the true WTP can be approximated by:

$$\Delta_{approx} WTP(r) = \frac{\partial WTP(r)}{\partial \gamma_L} d\gamma_L + \frac{\partial WTP(r)}{\partial \gamma_H} d\gamma_H \quad (13)$$

$$= -\frac{\frac{m_L^o}{m^*}}{\frac{m_H^o}{m^*} \gamma_H - 1} d\gamma_L + \frac{m_H^o}{m^*} \frac{\frac{m_L^o}{m^*} \gamma_L - 1}{(\frac{m_H^o}{m^*} \gamma_H - 1)^2} d\gamma_H \quad (14)$$

$$= \frac{-\frac{m_L^o}{m^*} (\frac{m_H^o}{m^*} \gamma_H - 1) d\gamma_L + \frac{m_H^o}{m^*} (\frac{m_L^o}{m^*} \gamma_L - 1) d\gamma_H}{(\frac{m_H^o}{m^*} \gamma_H - 1)^2} \quad (15)$$

To show that the approximation is a lower bound, we want to determine the sign of this expression and show that it is negative. First note that the denominator is positive; hence we can focus on the numerator to determine the sign of the overall expression. We will take the check-and-verify approach:

$$-\frac{m_L^o}{m^*}(\frac{m_H^o}{m^*}\gamma_H - 1)d\gamma_L + \frac{m_H^o}{m^*}(\frac{m_L^o}{m^*}\gamma_L - 1)d\gamma_H < 0 \quad (16)$$

and re-arranging:

$$\frac{m_L^o - m_H^o}{m^*}d\gamma_L + \frac{m_H^o}{m^*}(\frac{m_L^o}{m^*}\gamma_L - 1)(d\gamma_H - d\gamma_L) < 0 \quad (17)$$

Consider the two terms separately. The first term has two components. $m_L^o < m_H^o$ implies that the $\frac{m_L^o - m_H^o}{m^*}$ is negative. Moreover, we can show that $d\gamma_L$ is positive. The approximation sets $\gamma_L = 1$, and hence $d\gamma_L = 1 - \gamma_L$. Using the fact that $\gamma_L < 1$ proves that $d\gamma_L > 0$. The first term is therefore negative.

The second term has three components. The first two components are both positive: $\frac{m_H^o}{m^*} > 0$ because $m > 0$ and $(\frac{m_L^o}{m^*}\gamma_L - 1) > 0$ because $(\frac{m_L^o}{m^*}\gamma_L - 1) = \frac{B(1-t)}{m^*(1-t-\theta W)} \geq 0$. The sign of the final term therefore depends on the final component: $(d\gamma_H - d\gamma_L)$. Using $d\gamma_L = 1 - \gamma_L$ and $d\gamma_H = 1 - \gamma_H$ we can write this term as:

$$d\gamma_H - d\gamma_L = \gamma_L - \gamma_H = \frac{1}{1+e} \left[\left(\frac{m^*}{m_H^o}\right)^{\frac{1+e}{e}} - \left(\frac{m^*}{m_L^o}\right)^{\frac{1+e}{e}} \right] < 0 \quad (18)$$

where the last equality uses the definition of γ . We can sign this expression because $m_L^o < m_H^o$ and $e > 0$. Combining this result with the first term means that both terms in (17) are negative and hence:

$$\Delta_{approx} WTP(r) < 0 \quad (19)$$

This shows that the approximation is always smaller than the true WTP and hence

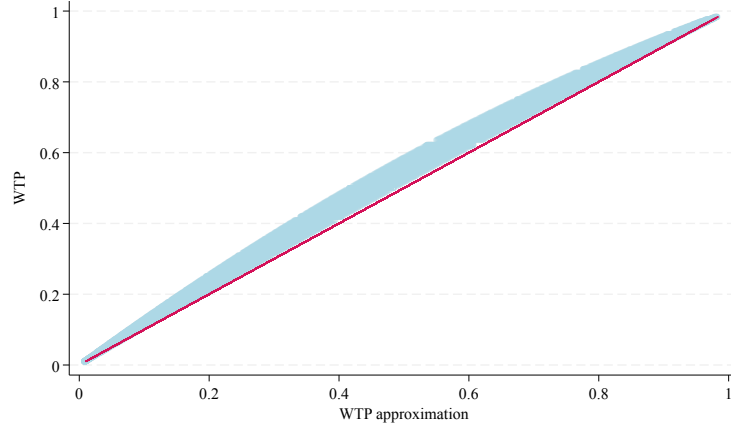
that the approximation is a lower bound for the WTP.

We now assess how tight this bound is and perform a simulation to compare the approximation to the true WTP for plausible parameter values.¹⁰ In our FPUC case B is \$600 and we run simulations varying the tax rate t between 0 and 0.9, θW between 0 and 0.91, spanning the full range of plausible values. We let m^* vary from \$200 to \$1,000, covering the eligibility thresholds in our sample states. For the labor supply elasticity, there exists a range of estimates from a very large literature on this parameter. The meta-analysis by Chetty (2012) concludes that a plausible estimate is around 0.25. Since there is substantial disagreement about this parameter, we use a wide range between 0.02 and 0.92, which includes most estimates.

Figure A3 shows the results and compares the WTP approximation to the true WTP value. The dots are close to the 45-degree line, meaning that the approximation performs extremely well. As we proved above, the approximation provides a conservative, lower bound, estimate of the WTP and the approximation values are smaller or equal to the structural WTP. In addition, the results show that the lower bound estimate is always fairly close to the true WTP and the approximation thus provides a tight bound. The maximum bias occurs at a WTP of 50 percent of earnings (a fairly high WTP). In this case, the worst approximation estimates WTP to be around 41 percent, even this worst-case scenario thus still provides a very reasonable approximation. On average the bias is 3 percentage points and thus substantially smaller. Using the approximation therefore comes at relatively little cost, but has the major advantage that it allows the researcher to be agnostic about the size of the labor supply elasticity.

¹⁰Note that equation (15) provides a closed form solution for the bias and could be used to assess the magnitude of the approximation bias. But the equation is hard to interpret and we therefore perform a simulation.

Figure A3: Performance of WTP Approximation



Note: The figure shows the results of the WTP approximation from equation (8c) in simulated data and plots the approximation and the true structural parameter. The 45-degree line presents the line of perfect fit. The fact that the true values lie above the 45-degree line reflects the fact that (8c) provides a lower bound estimate. The simulation uses the following parameter ranges $m^* \in [200, 1000]$, $t \in [0, 1]$, $\theta W \in (0, 0.91]$, $e \in \{0.05, 0.25, 0.50, 0.75, 1, 2, 3\}$.

D.2 Adjustment Frictions

A sizable literature discusses how adjustment frictions affect responses to budget discontinuities and proposes solutions to deal with such frictions (Chetty et al., 2011; Chetty, 2012; Kleven and Waseem, 2013; Einav, Finkelstein, and Schrimpf, 2017). In principle, any of these solutions could be applied to our setting. However, this is not required because our approach can handle frictions in a less parametric way and does not require correction methods that could be sensitive to assumptions (c.f., Einav, Finkelstein, and Schrimpf 2017).

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 frictionless benchmark, and η becomes: $\eta = \int_{m^*}^{m^o} d_0 = \alpha(m^o - m^*)d_0$. Now η depends on α and $(m^o - m^*)$, and multiple combinations of α and $(m^o - m^*)$ are consistent with the observed η . Note, however, that the impact of α cancels out in WTP estimates. We can re-write WTP in (7) as the ratio of excess mass in high (η_H) and low (η_L) risk settings:

$$WTP \approx 1 - \frac{\eta_L}{\eta_H} = 1 - \frac{\alpha(\tilde{m}^o - m^*)d_0}{\alpha(m^o - m^*)d_0} = 1 - \frac{(\tilde{m}^o - m^*)}{(m^o - m^*)} \quad (20)$$

Thus, α affects both the numerator and the denominator proportionally and cancels out. The WTP estimate is thus unaffected by the presence of standard adjustment frictions.

More complex adjustment frictions arise from indivisible shifts, in which workers can add or drop entire shifts but cannot adjust their labor supply by the minute, or when workers negotiate hours with their employer and can only choose from a limited number of shift options. Both of these scenarios are isomorphic in the model and create two distortions that affect the excess mass at the eligibility threshold. First, workers are unable to adjust their labor supply exactly to the threshold earnings m^* , and instead have to reduce their earnings more to become eligible for $\mathcal{B}$. Second, some workers may be deterred from responding to the threshold because the indivisibility friction would force them to take a large earnings cut. Workers are thus less responsive to the threshold than in the frictionless benchmark.

Addressing the first challenge is relatively straightforward. The excess mass, η , now spreads over a wider earnings range. 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 to our approach.¹¹ In other words, the first challenge affects the estimation strategy but does not affect the link between 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 $(1 - \alpha)$ is constant, equation (20) applies again and implies that the WTP estimate is unaffected by this friction. Our framework thus identifies WTP , even if there are indivisibility constraints and hours decisions are not fully flexible.

¹¹Canonical bunching methods focus on excess mass right at the threshold and would fail to fully capture more spread-out excess mass.

D.3 Cobb-Douglas

Consider a case where utility is non-separable in health and cost of effort $U\left(T(m), \frac{m}{z}, a\right)$ ($= U\left(T(m), g\left(\frac{m}{z}, a\right)\right)$) and take the Cobb-Douglas case with $g\left(\frac{m}{z}, a\right) = m^\alpha h^{1-\alpha}$. The FOC becomes:

$$1 - t - \Delta t = (1 - r)\alpha \left(\frac{a_0}{m}\right)^{(1-\alpha)} + r\alpha \left(\frac{a_1}{m}\right)^{(1-\alpha)} + \theta[m^\alpha a_1^{1-\alpha} - a_0^{1-\alpha}] \quad (21)$$

From $u(m^o, a_1) = u(m^o - W(m), a_0)$ we can derive an expression for a_1 :

$$m^\alpha a_0^{1-\alpha} = W(m) + m^\alpha a_1^{1-\alpha}$$

Substituting this in equation (21) and simplifying yields:

$$1 - t - \Delta t - (1 + \alpha)\theta W(m) = \alpha \left(\frac{a_0}{m}\right)^{(1-\alpha)}$$

Notice that the implicit tax imposed by the health risk increased by factor α relative to the separable case. This additional cost arises from the health effect on the marginal utility of leisure. A second change is that the marginal cost of a health shock increases the more a worker works ($m \uparrow$). And the value of health (W) now depends on the level of earnings m . This non-linearity in the cost of health shocks makes health risks operate like a non-linear progressive tax system, with increasing cost at higher m .

D.4 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. Struc-

tural 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 introducing income effects implies that excess mass does not only appear at m^* but also at lower earnings levels.

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

$$\tilde{m}^o = \tilde{z} + e\tilde{w} - \gamma\tilde{y} \quad (22)$$

$\tilde{x}$ indicates log values for x and w is the wage $\gamma\tilde{y}$ 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 $\mathcal{B}$ reduces labor supply if $\gamma < 0$. This effect changes the impact of the non-linear benefit schedule studied above. For a worker with earnings ε above the eligibility notch, introducing $\mathcal{B}$ reduces labor supply to $m^* + \varepsilon - \gamma\mathcal{B}$ which is below m^* if ε is small. The labor supply response thus creates excess mass below m^* and the excess mass at the notch point therefore does not fully capture the labor supply response. Hence, with income effects, excess mass (η) does not appear only at m^* but spreads out across a broader range of earnings. This creates additional identification challenges and we will return to the issue below.

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

$$\eta = \int_{m^*}^{m^* + \Delta m} d_0 dm$$

$$\Delta m = \eta / d_0 \quad (23)$$

where d_0 is the pre-notch earnings distribution between m^* and $m^* + \Delta m$, and to keep

notation simple, we assume that d_0 is constant over this segment.¹²

To compute Δm we need to estimate d_0 and η . If data on the pre-notch distribution is available, we can compute d_0 directly from this data.¹³ A second step is to estimate η , the extra mass generated by bunching individuals. η is the difference between the observed post-notch earnings distribution (d_1) and the distribution of non-bunchers (d'_0):

$$d_1 = \eta + d'_0, \quad (24)$$

While we observe d_1 , d'_0 is not directly observed and needs to be estimated. Typically $d'_0 \neq d_0$ and the pre-distribution does not provide a valid counterfactual. To see why, consider workers at m^* in the pre-period, they are below the eligibility threshold and thus part of the non-bunchers. Without income effects, their behavior would be unaffected by a lump sum benefit payment $\mathcal{B}$ and the pre-benefit distribution is a valid estimate for the frequency of this group. However, with income effects $\mathcal{B}$ reduces the labor supply of this group to $m^* - \gamma\mathcal{B}$ and no non-buncher is working at m^* after the introduction of $\mathcal{B}$. Now the pre-benefit distribution of earnings d_0 is a bad counterfactual for the distribution of non-buncher after the launch of $\mathcal{B}$ because $d'_0(m^*) = 0 \neq d_0(m^*)$. Using d_0 as counterfactual will bias the results, $d'_0(m^*) = 0$ implies that *all* individuals at $m = m^*$ are bunchers and the spike in density above neighboring cells ($\hat{\eta} = d_1(m^*) - \hat{d}_0(m^*) < \eta$) 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

¹²This assumption simplifies notation but is not required and richer baseline distributions can be included in the estimation.

¹³Without data on the pre-period, d_0 can still be estimated with “untreated” earnings ranges away from the notch point. This requires estimating d_0 in such untreated earnings ranges and then extrapolating to earnings levels in the treatment range. The researchers will need to make an assumption about which earnings 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 threshold, making it harder to define untreated earnings bins.

the interpretation of the elasticity as (un)compensated but additionally bias the labor supply response estimate itself.

Valid estimates can be obtained with a difference in difference analysis. A first advantage of the difference-in-differences 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 $d'_0 \neq d_0$. When leisure is a normal good ($\gamma < 0$), 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:

$$\int_0^{m^*} d'_0 = \int_0^{m^*} d_0 \equiv \pi$$

Using this result in (24), we can show that the notch generates total excess mass:

$$\int_0^{m^*} \eta = \int_0^{m^*} d_1 - \int_0^{m^*} d_0$$

which is the difference in the total density below the notch before and after the notch reform. $\int_0^{m^*} \eta$ 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:

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

where t^* is the time of the reform, π is captured by the coefficient on the dummy $\mathbb{1}[m < m^*]$. The coefficient $\bar{\eta}$ captures the average rise in density below m^* . Substituting this estimate into (23) 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, the 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 η coefficient vary across earnings ranges:

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

Plotting η_m provides a visual check on the assumption that the notch generates excess mass. The excess mass should peak at m^* , and its mirror image, missing mass, should peak above 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.

D.4.1 Compensated Elasticity

The observed uncompensated labor supply elasticity reflects both an income and a substitution effect. The canonical bunching approach assumes that the latter is zero and that compensated and uncompensated elasticities coincide. In the more general case, we need to know the income effect γ to quantify the compensated elasticity from observed uncompensated elasticities. With this additional unknown parameter we require one additional moment condition. This section will show that the dispersion of excess mass away from m^* can be used as an extra moment condition. Without income effects all excess mass would arise at m^* , while the excess mass is more spread out over larger earnings ranges the bigger the income effect.

To derive a solution for γ , we take advantage of the location of the bunching. Note that all bunchers below m^* are at an interior solution, we call them “interior bunchers”. At the earnings level m^* , there are several individuals who are at a corner solution and

one individual for whom m^* is an interior solution; call this person the marginal buncher from the left. Before the notch the earnings of this person were $d_0 = m^* + p$. And using those two labor supply decisions in (22), we can show that:

$$m^* + p - \tilde{z} - e\tilde{w} + \gamma\tilde{y} = m^* - \tilde{z} - e\tilde{w} + \gamma(\tilde{y} + \mathcal{B})$$

$$\gamma = p/\mathcal{B}$$

We can thus solve for γ by deriving p . Notice that everyone with $d_0 \leq m^* + p$ is an interior buncher and the total mass of interior bunchers is thus:

$$I = \int_{m^*}^{m^*+p} d_0$$

The excess mass below the notch point (I) thus pins down p , e.g. with d_0 constant $p = I/d_0$. And using p , we can solve for $\gamma = \frac{I}{d_0\mathcal{B}}$. 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 Robustness Checks

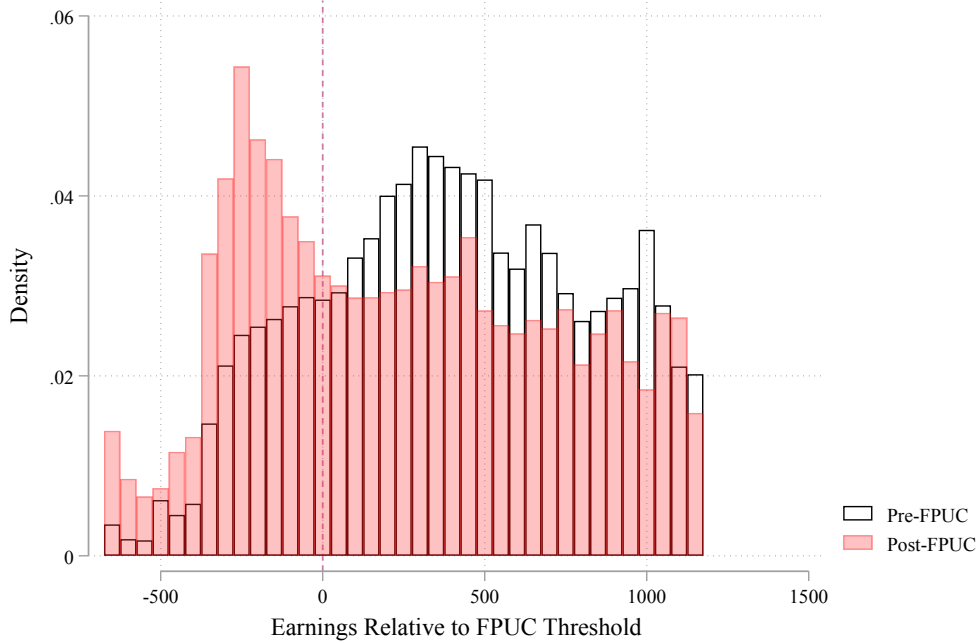
E.1 Raw Earnings Density before and after Covid

The figure below shows the distribution of weekly earnings around the budget notches before and after the start of Covid. Since the thresholds are at different income levels in different states, we stack the densities from all states and show the distribution relative to the threshold level denoted by 0. All states are given equal weight in this figure. We show the density for a window from \$600 below to \$1,200 above the threshold

earnings. Negative x-axis values indicate earnings below the threshold and positive values earnings above the threshold. In line with the main results, we show results for the pre- and post-period (defined by C_t). Both densities integrate to 1, so we ignore any mass outside the window. The timing of Covid and the start of FPUC coincide almost perfectly, so we use those two terms interchangeably.

Figure A4 shows substantial excess mass below the earnings threshold in the post-FPUC period. There is no excess mass before FPUC was introduced. In line with the regression results, we see that excess mass is strongest near but below the earnings threshold and similarly the missing mass is most pronounced near but above the threshold level. The difference between the pre and post densities aligns closely with the regression coefficients shown in the main text.

Figure A4: Earnings Distribution Around FPUC Threshold



Note: The figure shows the earnings distribution before and after the beginning of FPUC. Pre-FPUC is the period defined by $C_t = 0$ and post-FPUC implies $C_t = 1$. The figure stacks distributions from the sample states for a window from \$600 below to \$1,200 above the FPUC eligibility threshold. To give each state threshold equal weight in the figure, we weight observations by the density at the absolute earnings level in the pre-FPUC period. Observations in the tails of the absolute distribution thus get a higher weight. The two densities integrate out to 1.

E.2 Border Design

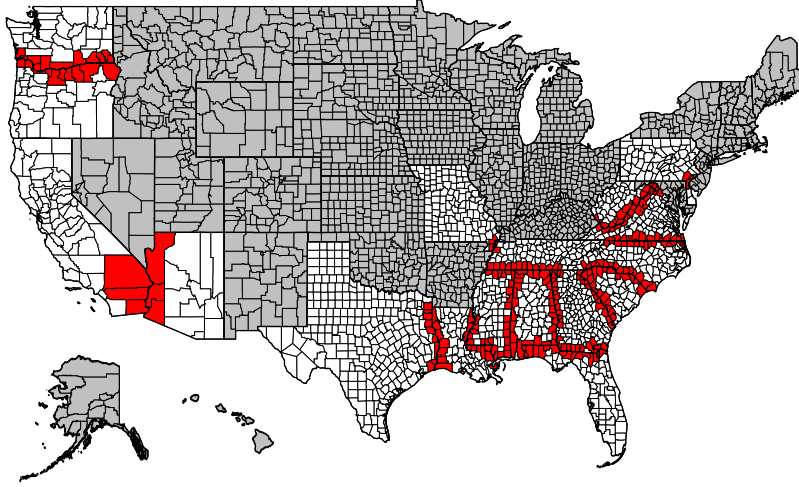
In this section we narrow our sample to counties along state boundaries, and thus with similar characteristics but facing different UI eligibility rules. The border counties are shown in Figure A5. These border communities generally have integrated labor markets and thus share many of the same demand shocks. 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 is comprised of observations from 21 states, between which there are 24 state borders. In the border sample we exclude borders where we don't have data from border counties on both sides, which leaves us with the 17 unique state borders highlighted in Figure A5.

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 A4). 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 its own DiD experiment and we stack the 17 border DiDs into a single regression. The results are again close to our baseline estimates (Column 2).

E.3 Labor Supply Elasticity

We estimate labor supply elasticities at the industry level to use as a control variable in the main analysis. These estimates regress log hours worked on hourly wage changes at the worker level. A concern with the OLS regression is that wage changes are endogenous and capture promotions or changes in worker productivity. We therefore use firm-wide wage updates as instrument. This, for example, captures that many firms update all worker wages at once at regular intervals. The firm-wide wage change is built by taking the average wage change among all workers at the firm, excluding

Figure A5: Border Counties in Sample



Note: The figure shows counties along the state borders that are included in our border sample. There are in total 17 borders for which we have data from counties on both sides of the border.

Table A4: Excess Mass around UI Eligibility Threshold - Border Counties Sample

	(1)	(2)
Excess Mass (ptp)	0.96*** (0.15)	0.91*** (0.15)
Interact income x time FE with		border IDs
Observations	686,692	686,692
Sample	Border	Border
Controls		Pairwise

Note: The Table reports results from equation (10). The border sample is restricted to counties at state borders shown in Figure A5. Source: Homebase.

the focal worker (leave one out). The measure has several advantages. An important feature is that it is based on hourly wages, rather than weekly earnings. The wage measure thus avoids a mechanical relation of wages and work hours. Second, our firm-wide wage change is unaffected by compositional changes since it takes the average of worker level wage changes. Employee turnover thus doesn't affect our measure of firm wage changes. The analysis is restricted to the pre-COVID19 period.

The first stage is extremely strong with a first stage F-statistic of 10,000. This shows that wage changes among co-workers are a strong predictor of an update to my own wage. One concern might be seasonally patterns. If most firms change wages in January and January is a low hour month, the elasticity estimates would be biased downward. We find that controlling for month fixed effects doesn't change the results, suggesting that seasonality doesn't bias the results.

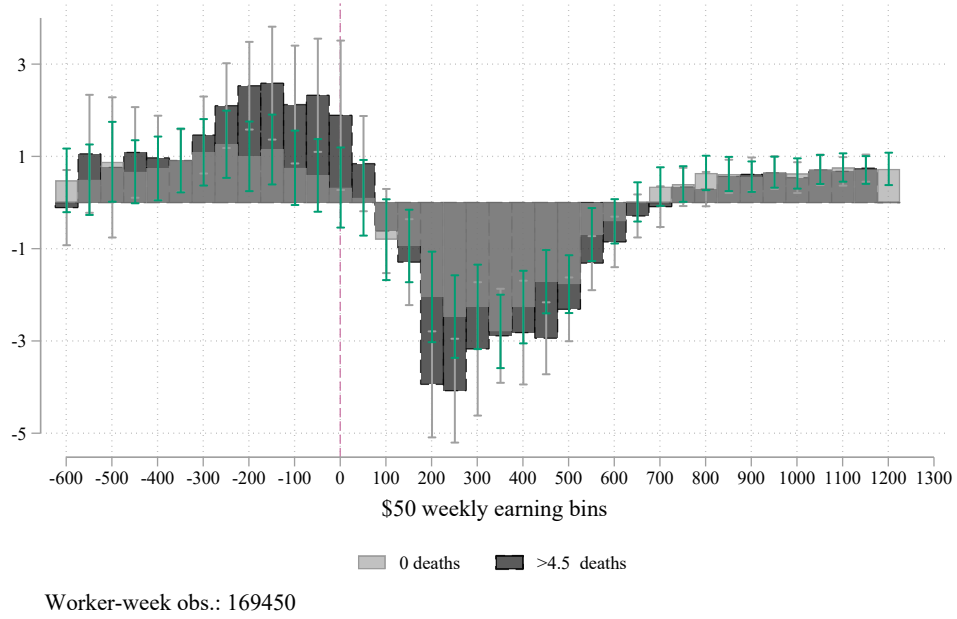
Finally, we estimate the 2SLS regression and allow for different elasticity coefficients by industry. Specifically, we estimate several 2SLS regressions, one each per two digit NAICS code. To preserve power, we aggregate ten industries with fewer than 1,000 observations into an "other" category. The elasticity of the median industry is 0.86.

E.4 Alternative Measure of COVID-19 Exposure

In this section, we estimate the labor supply response to the increase in workplace risk using an alternative measure of COVID-19 exposure θ_{tci} and use the local COVID-19 fatality rate in the county, measured as in deaths per 100,000 people.

In Figure A6, the excess/missing mass in grey represents the behavioral response to FPUC in counties with zero recorded new deaths and the black area represents the “magnified response” in very high-risk settings (more than 4.5 weekly new deaths per 100,000 people). The excess mass in these high-risk settings is visibly larger, consistent with the results presented in Figure 6.

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



Note: The figure shows η^k coefficients from equation (10) for the highest and lowest levels of COVID-19 risk (θ_{tci}). Different from Figure 6 θ_{tci} is measured in deaths per 100,000 in the week in the local area. The gray bars represent the response in area-weeks with no new deaths and black bars in areas with more than 4.5 deaths per 100,000. The other details are the same as in Figure 6.

E.5 Sample Selection and Extensive Margin

In this section, we explore alternative samples and show that the results are robust to alternative choices. The baseline sample studies weeks with positive earnings among more attached workers who are employed by the same establishment before and after the onset of the pandemic. In the baseline sample, we additionally ensure that the earnings distributions before and after the onset of the pandemic are based on the same number of observations by using a window of 15 pre- and 15 post-weeks. For workers with a missing week, we keep an equivalent shorter symmetric window (e.g. a worker with 13 pre- and 15 post-weeks, we keep 13 weeks on both sides of the pandemic onset). This symmetry restriction guarantees that changes in excess and missing mass are not driven by exit effects but by workers moving up or down in the earnings distribution.

In this Appendix, we show WTP estimates for alternative samples, relaxing each of the restrictions above. Column (1) of Table A5 uses the baseline sample and replicates the baseline estimate from the main analysis. Column (2) relaxes the symmetry restriction and allows workers to have more work weeks before or after the pandemic. This leaves the total number of workers unchanged but extends the number of observations (i.e., worker-weeks). In Column 3, we add workers with less workforce attachment and include workers whom we observe exclusively before or after the onset of the pandemic. This doubles the number of workers and worker-week observations relative to our baseline specification. Panel A shows that the results remain very close to the baseline estimates.

We next consider extensive margin responses. For workers who leave the Homebase data, we cannot tell whether they stopped working or started a new job outside the Homebase sample. In the baseline analysis, we thus exclude exits and focus on the intensive margin of hour adjustment. In Panel B row 1 we add a zero-earnings week at the end of the work spell for workers who leave the data. The estimate is similar and

in line with potential measurement error, slightly attenuated with a WTP of 23%.¹⁴ In row 2, we take a more conservative approach and only include temporary exits in the analysis. It seems more likely that temporarily absent workers remained with the Homebase employer and the absence from the data are true zero earnings weeks. Using this in the analysis, we again find similar results to the baseline. In line with reduced measurement error, the effects are slightly larger than before at 26%. Finally, row 3 of Panel B combines the two extensive margin approaches and yields a WTP estimate of 24%. The results thus remain in the same ballpark for alternative sample choices.

Table A5: WTP Estimates with Expanded Samples

	(1) Baseline	(2) Asymmetric Sample Window	(3) Less Attached Workers
A - Intensive Margin	0.303	0.295	0.285
Worker weeks	169,450	228,591	315,566
Workers	9,063	9,063	21,418
B - Extensive Margin:			
1) zero earning for last week	0.226	0.216	0.226
Worker weeks	177,108	236,249	331,805
Workers	9,063	9,063	21,418
2) zero earnings for temporary absences	0.260	0.235	0.241
Worker weeks	182,350	241,749	333,648
Workers	9,063	9,063	21,418
1) + 2) zero for inner and last week	0.237	0.215	0.232
Worker weeks	186,183	245,324	345,003
Workers	9,063	9,063	21,418

¹⁴An additional reason why the results are smaller than the baseline is that at corner labor supply solutions, the WTP approach may yield a lower bound of the true WTP.

F Transmissible vs. Non-Transmissible Health Risks

This section analyzes the difference between the WTP for a transmissible illness (with externalities) and a non-transmissible one. 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 transmissible (WTP_T) and a non-transmissible 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-household secondary infection fatality rate is $s = 0.002$ and assume that the worker cares as much about others' utility as her own ($\Omega = 1$).¹⁵ For household size, consider a four-person household, i.e. a household at the 90th percentile of the US size distribution (three other household members: $n = 3$). 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 30.3% would be reduced to roughly $30.3\% / 1.006 = 30.1\%$ of weekly earnings for a non-transmissible disease. While the Infection Fatality Rate (IFR) captures the actual risk of death across all infections, the Case Fatality Rate (CFR) may better reflect perceived risk if individuals base their decisions on diagnosed and reported cases. CFR estimates in the literature range from 1% to 12.7%. Assuming individuals respond to the highest CFR estimate of 12.7% (Villa, Myers, and Turkheimer, 2020), the intra-household secondary infection fatality rate increases to $s = 0.038$, and the WTP for a non-transmissible health risk would decrease to 26.3%. Even under this extreme upper bound for transmission-related risk, concern for one's own health remains the dominant component of the WTP estimate, with only a modest additional contribution from pro-social concerns.¹⁶

¹⁵ s is obtained multiplying the 30% intra-household transmission rate (Lewis et al., 2020) with the 0.68% infection fatality rate (IFR), that is the fatality rate conditional to being infected estimated by the meta-analysis by (Meyerowitz-Katz and Merone, 2020). IFR values range between

¹⁶Pro-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 quite small.

G Hedonic Regression

Table A6 shows a hedonic wage regression. This specification regresses log hourly wages on the weekly risk variable used throughout ($\theta_{o,i,t}$) and individual fixed effects. A one standard deviation increase in risk is associated with a wage increase of 0.4%.

Table A6: Hedonic Regressions

	(1)
$\theta_{o,i,t}$	0.004*** (0.0002)
Person FE	X
Avg(hourly wage)	18.35
Observations	169,450
Standard errors in parentheses	
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

H The Value of Enjoyable Jobs

A strength of the WTP approach is that it can be used widely for different types of amenities. To illustrate this, we present a second case study that estimates the value of enjoyable work. Enjoyment of work scores are widely collected in labor market surveys and provide information on the perceived quality of work. Yet, it is hard to interpret categorical enjoyment scores without a money metric for these scores. Work enjoyment can be affected by various factors and captures an aggregate (net) value of amenities in a given job. This value of “good” and “bad” jobs has been central in labor economics (for an overview, see Lavetti (2023a)).

The empirical strategy analyzes bunching around the U.S. early retirement age threshold. Workers accumulate social security entitlements for each quarter worked and once they reach age 62 the marginal value of additional quarters changes, creating

a kink in the lifetime budget constraint.¹⁷ At age 62 individuals also become eligible to claim retirement benefits, potentially alleviating liquidity constraints. We restrict the sample to individuals with sufficient savings to delay retirement and exclude people with less than a year’s income in savings to mitigate the impact of the liquidity channel. We then study how bunching at the 62 age threshold differs for workers in high and low-enjoyment jobs. An important limitation relative to the workplace safety application is that we lack panel data and now use cross-sectional data comparing individuals with different job enjoyment. To interpret this heterogeneity, we must ensure that both groups of workers would behave similarly if they held similarly enjoyable jobs.

The analysis uses data from the US Health and Retirement Survey (HRS) between 1992 to 2018. Figure A7 plots retirement rates per quarter and shows that there is substantial bunching at the age 62 threshold.¹⁸ The figure plots retirement rates separately for workers in enjoyable and less enjoyable jobs.¹⁹ During ordinary quarters, around 2% of satisfied workers retire, while this rate spikes to around 10% in the quarter they turn 62 (Panel A of Table A7 shows excess mass estimates). Using these estimates in the traditional bunching framework implies that workers who enjoy their job retire $(0.1-0.02)/0.02=4$ quarters early because of the kink. The opportunity cost of reducing work time is smaller for individuals who enjoy their work less, and as predicted in our model, they indeed respond more to the kink. Their excess mass jumps to 15%, implying that workers in less enjoyable jobs retire $(0.14-0.02)/0.02= 6$ quarters earlier and reduce their retirement age by 2 quarters more than workers who

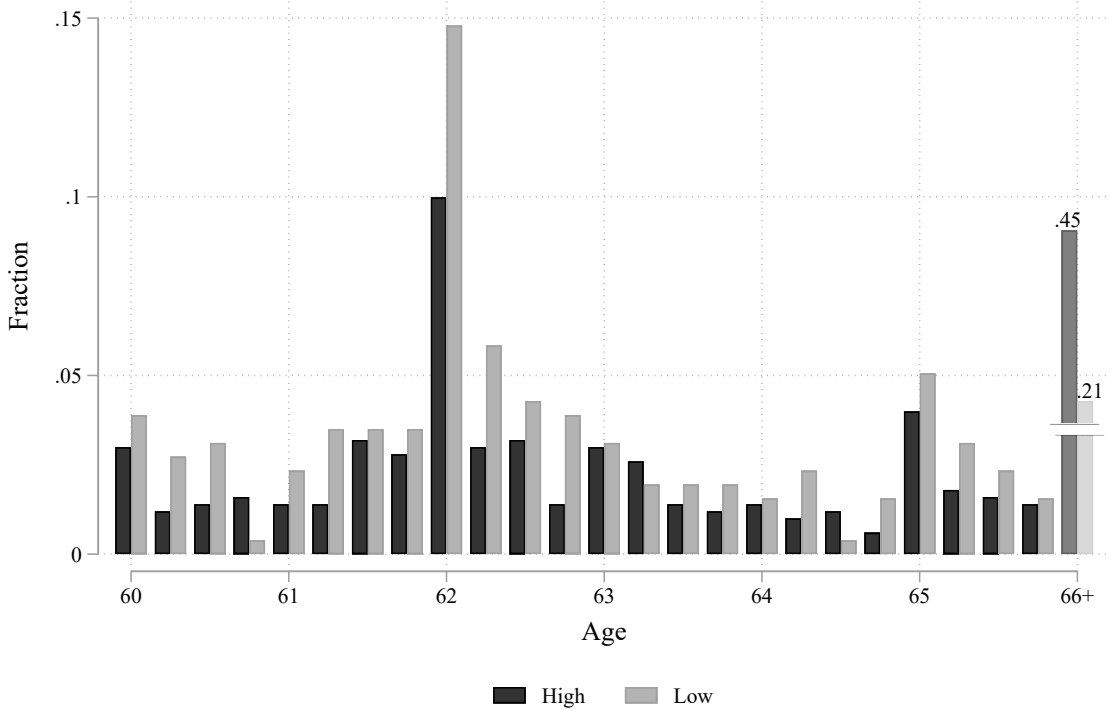
¹⁷Each additional month worked beyond 62 increases the retirement benefit by 0.4%-0.6% until individuals reach the full-benefit retirement age (65-66 depending on birth year). The rewards for working extra months beyond this age are 0. 5% - 0. 8%. It is important to note that only convex kinks generate bunching. While in principle, it is ambiguous whether the kink in the lifetime budget constraint at age 62 is convex (the answer depends on the replacement rate, life expectancy, and the discount rate), in our context, an overwhelming majority of individuals do face a convex kink, and we, therefore, treat the kink as convex.

¹⁸We restrict the sample to people who were in the workforce before turning 60. The figure shows the share of this restricted sample retiring each quarter.

¹⁹Enjoyment is measured in the previous year. If data are missing (12% of cases) we use the next closest year we have data. High enjoyment are people who strongly agree with the statement, “I really enjoy going to work.” Workers who disagree or strongly disagree are coded as not enjoying their work.

are enjoying their jobs (see Panel B). Using these results in the WTP formula from above, we find that an enjoyable job is worth an extra $(6-4)/4 / 4 = 12.5\%$ of annual income (see Panel C). On average, a worker would thus accept a 12.5% wage cut to move from a less enjoyable job to a more enjoyable one.²⁰

Figure A7: Retirement Age by Work Enjoyment



Note: The figure shows the share of people retiring at any given age among people who had not retired by age 60, separately for those with high and low work enjoyment before retiring. The last bar shows the share of people who had not retired by age 66.

We probe the importance of confounders that could give rise to spurious differences in retirement patterns. We interact all controls with age to allow for different retirement patterns across the demographic groups. The first strategy introduces industry fixed effects to absorb industry-wide retirement practices and exploits variation in enjoyment *within* a given industry. The results remain similar to the baseline (see Table

²⁰We are not aware of a directly comparable estimate. Work that estimates the importance of non-wage amenities for inequality found that amenities explain between 15% and 26% of inequality (Lavetti (2023a); Taber and Vejlín (2020); Sorkin (2018)).

Table A7: Effect of Work Enjoyment on Retirement

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High Work Enjoyment						
Excess Mass at Age 62	0.079 (0.014)	0.078 (0.014)	0.079 (0.014)	0.078 (0.014)	0.079 (0.014)	0.079 (0.014)
Panel B: Low Work Enjoyment						
Excess Mass at Age 62	0.119 (0.023)	0.118 (0.023)	0.119 (0.023)	0.119 (0.023)	0.119 (0.023)	0.120 (0.023)
Panel C: WTP for Enjoyable Work						
% of income	0.125	0.127	0.125	0.130	0.126	0.127
FE, interacted w/ age		industry	health	occupation	location	education
Observations	18192	18096	18192	18120	18179	18168

Note: The table shows how work enjoyment affects the likelihood of retiring at age 62 (first three months), which is when workers become eligible for social security benefits. The baseline specification (1) shows results from a pooled OLS regression on a balanced quarterly panel of 18192 individuals aged 60-65. Only people who had not retired by 60 are included. We exclude people with less wealth than annual income before age 60. The dependent variable is an indicator for the age of retirement. Panel (A) shows the additional mass retiring at the threshold age among people with high enjoyment of work, and panel (B) among those with low enjoyment. Columns (2) to (6) show the results when controlling for industry, general health level, occupation, region-division of residence, and years of education. All specifications include a linear age control and a dummy for retiring at 66 or later.

A7, Column 2). Similarly, adding proxies for health has little impact on the results, suggesting that our threshold design is orthogonal to variation in health (column 3). Next, we add several proxies for human capital. Adding occupation-fixed effects again has little impact on the results (column 4). Proxies for education and location also have little impact on the results (columns 5 and 6).²¹

²¹A further potential concern is inflated bunching at the eligibility threshold from delayed retirement reporting. Individuals have little incentive to report a retirement age before the age of 62 to the Social Security Administration since it would not lead to additional benefits, potentially resulting in a spike in reports at age 62. Instead of admin data reports, we use survey reports on the age people stop working, which is less likely to suffer from target-date reporting problems.

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