Online Appendix

Job Displacement Insurance and (the Lack of) Consumption-Smoothing

by François Gerard and Joana Naritomi

Online Appendix A: Additional Tables and Figures

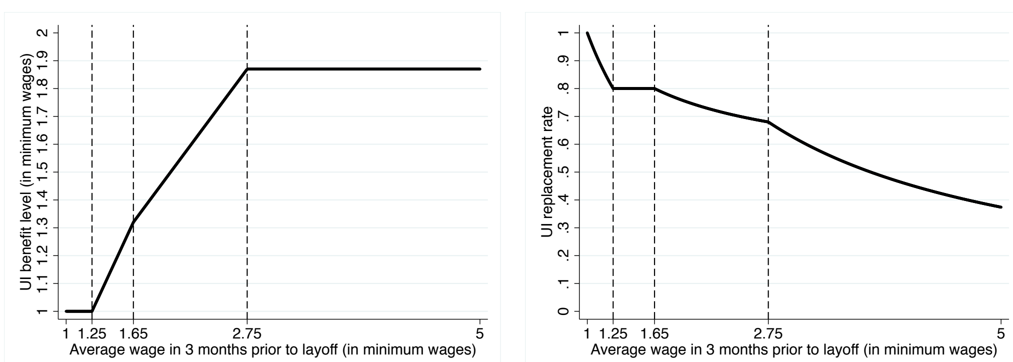
Full schedule of UI benefits in Brazil. The UI benefit level depends on a displaced formal worker's average wage in the three months prior to layoff and ranges from 100% to 187% of the minimum wage. Define w the displaced formal worker's average nominal wage in the three months prior to layoff expressed in multiples of the prevailing minimum wage (mw). Her UI benefit level (b) is then calculated as follows:

- $b = mw$ if $w < 1.25$
- $b = .8\ w$ if $1.25 \leq w < 1.65$
- $b = 1.32\ mw + .5\ w$ if $1.65 \leq w < 2.75$
- $b = 1.87\ mw$ if $w \geq 2.75$

Figure A1 displays the relationship between w and b graphically, as well as the replacement rate (b/w).

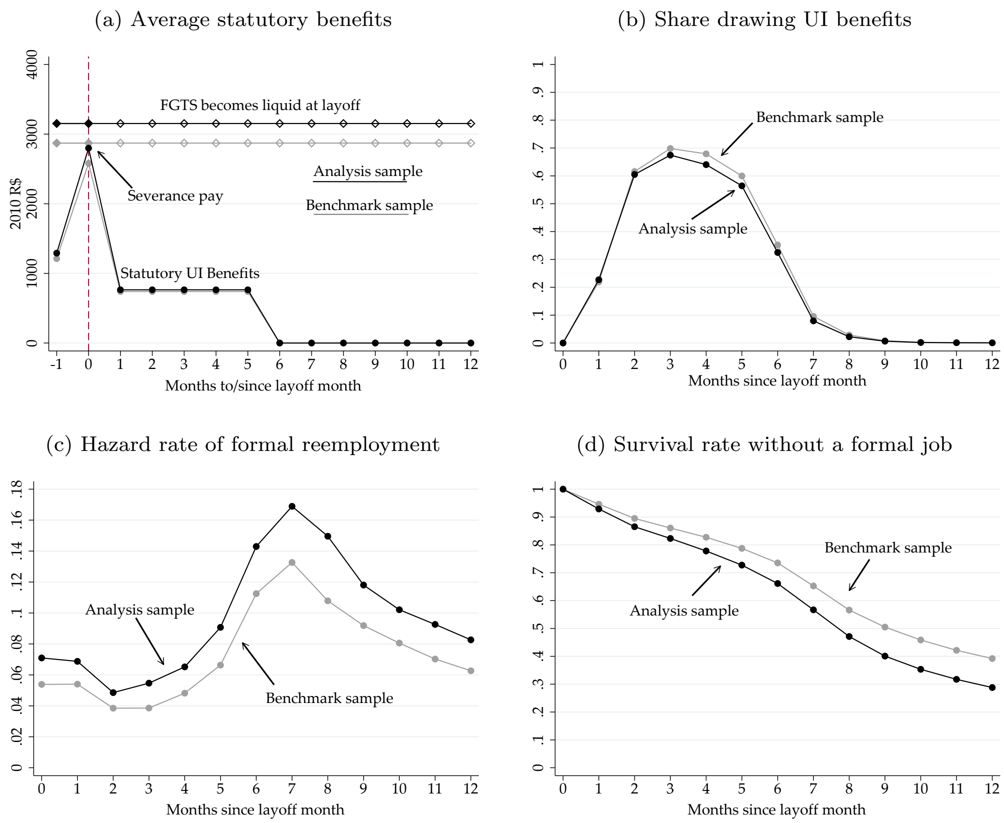
Figure A1. : UI benefit level and replacement rate schedule in Brazil

(a) UI benefit level (b) UI replacement rate



Notes: The panels display the UI benefit level and the UI replacement rate in the Brazilian UI program, which is a function of a displaced formal worker's average nominal wage in the three months prior to layoff, expressed in multiples of the prevailing minimum wage. The replacement rate in this figure uses the gross wage (rather than the net wage as in Table 1), which is used to calculate the UI benefit level.

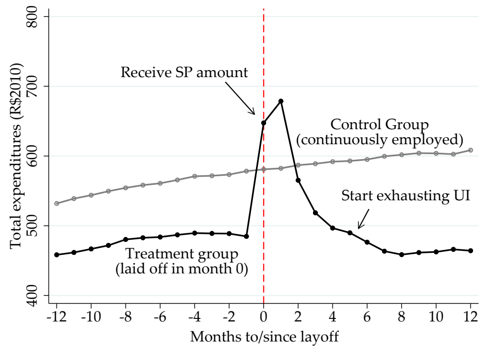
Figure A2. : Background information and representativity of the analysis sample (workers laid off in 2011)



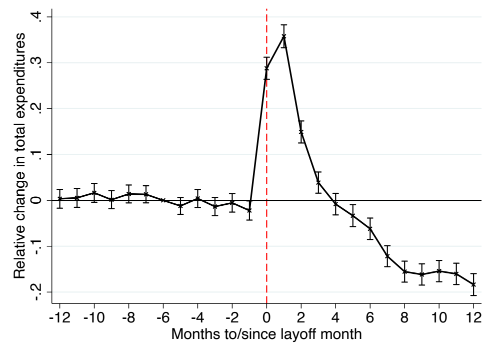
Notes: The samples in Figure 2b are restricted to workers laid off in 2011 such that we observe their full UI spell in the UI data. We show in this figure that the patterns in Figures 2a, 2c, and 2d are similar when we restrict the sample to 2011 (we replicate Figure 2b in panel b).

Figure A3. : Additional results and robustness checks

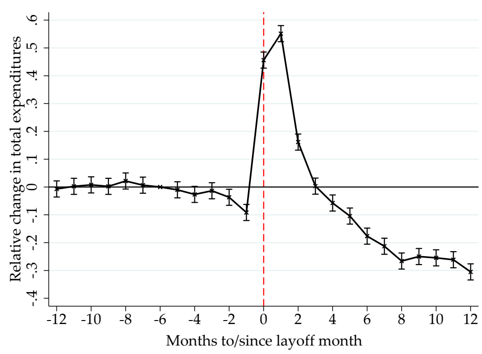
(a) Treatment vs. control (raw averages, only netting out month fixed effects; unconditional sample)



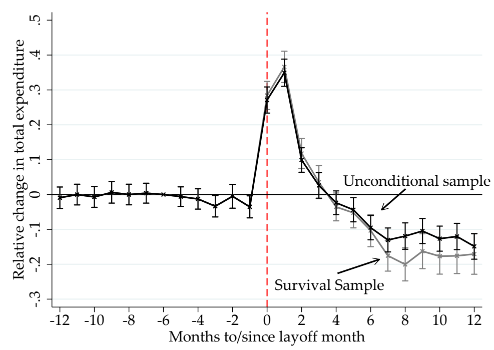
(b) Main DD estimates - conditional sample (workers not reemployed by month 12 after layoff)



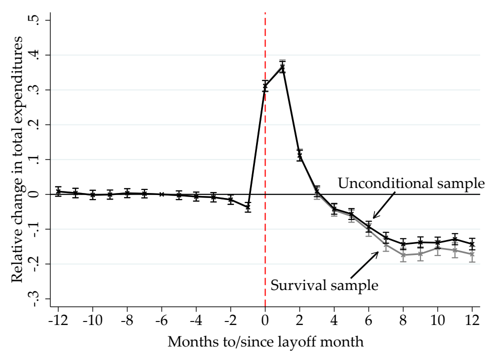
(c) Main DD estimates - Median regression (using the unconditional sample)



(d) Main DD estimates - layoffs from downsizing firms (lost at least 30% of workforce in layoff year)



(e) Main DD estimates - Reweighing based on distribution of observables in the benchmark sample



Notes: The figure presents robustness checks for the main results in Figure 4a. Panel (a) displays the average monthly expenditures in each of the 25 months around the layoff event for the treatment and control groups, separately (raw data, we only net out calendar month fixed effects). Panel (b) presents DD results (point estimates and 95% confidence intervals) restricting the treatment group to workers not yet reemployed by month 12 after layoff. Panel (c) presents DD results for the median. We cannot control for month and worker-event fixed effects in this case, so we focus on the unconditional sample. Panel (d) presents DD results restricting the treatment group to workers laid off from a firm that lost at least 30% of its workforce in the layoff year. We also restrict attention to firms (i) with at least 10 employees 12 months before layoff, (ii) that had not been downsizing in the year prior to the year of layoff, and (iii) that remained smaller in the year following layoff. Panel (e) presents DD estimates reweighing both the treatment group and the control group to match the distribution of observables (wage and SP amount at layoff, age, education, gender) in the benchmark sample described in column (2) of Table 1.

Figure A4. : Additional results for Laid-off vs. Fired in Figure 4b

(a) Laid-off vs. Fired (survival sample) (b) Survival rates for Laid-off vs. Fired

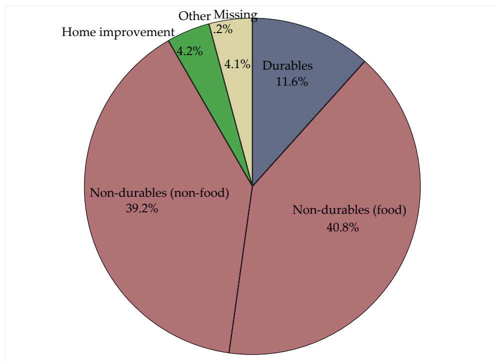
Notes: The figures present results complementing the evidence in Figure 4b. Panel (a) shows similar results as in Figure 4b using the survival sample. Panel (b) displays the estimated survival rates in non-employment for laid off and fired workers. The survival rates are higher for laid off workers while they are eligible for UI, but they converge quickly after UI exhaustion, which is consistent with UI job-search disincentives. We plot point estimates and 95% confidence intervals.

Figure A5. : Total expenditure profile around reemployment events

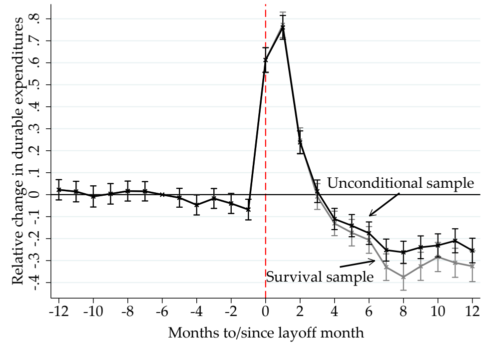
Notes: The figure presents DD results for the change in expenditure levels around reemployment. Panel (a) uses laid-off workers who were reemployed in months 0 to 10 after layoff as our treatment group such that all reemployment events have at least two months in the *post* period. We use laid-off workers who remained without a job 12 months after layoff as our control group. We randomly assign a "placebo" reemployment event to these workers, respecting the distribution of reemployment events across the months 0 to 10 after layoff in the treatment group. We then keep the observations in the 5-month window centered around the (placebo) reemployment event. The control group allows us to net out overall changes in expenditures – unrelated to reemployment – in the months after layoff. We then follow a similar specification as in equation (1): we regress monthly expenditures on worker-event fixed effects, event time fixed effects (here we have $k = -2, ..., 2$ and we use $k = -1$ as reference month), month fixed effects, and event time fixed effects interacted with a dummy variable for being in the treatment group. We plot the estimated coefficients on these interactions (point estimates and 95% confidence intervals) in relative changes, dividing our estimates by the mean in the treatment group in the reference month. All samples are also reweighed such that they compare better to the overall sample of laid-off workers (as in the other empirical analyses; see Section II.A for more details), and we cluster standard errors by worker. Panel (b) displays results from a regression in which we only include the subset of workers reemployed in months 8-10 after layoff (when all job displacement insurance benefits have been exhausted).

Figure A6. : Additional results by expenditure categories as in Figure 6

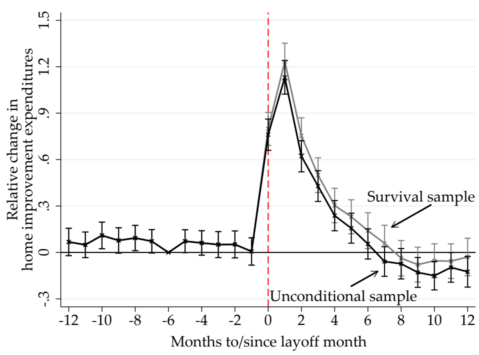
(a) Composition of expenditures (control group



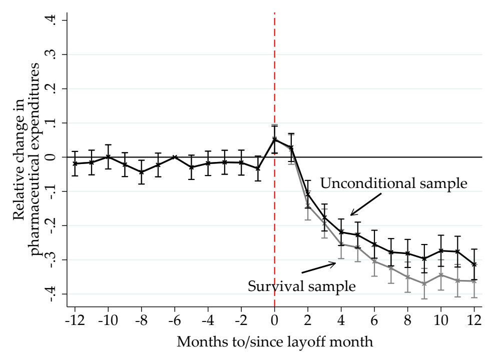
(b) DD estimates for durables



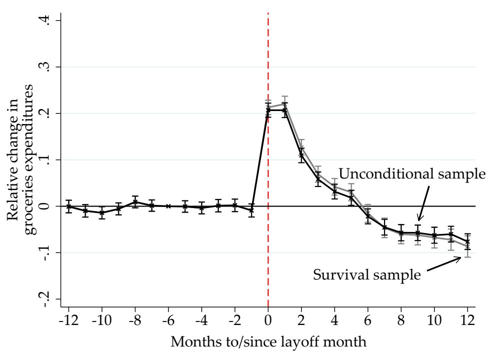
(c) DD estimates for home improvement



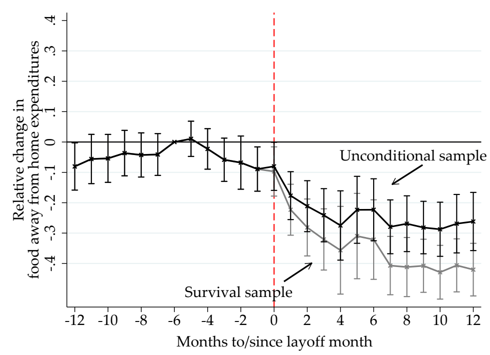
(d) DD estimates for pharmacy expenditures



(e) DD estimates for groceries



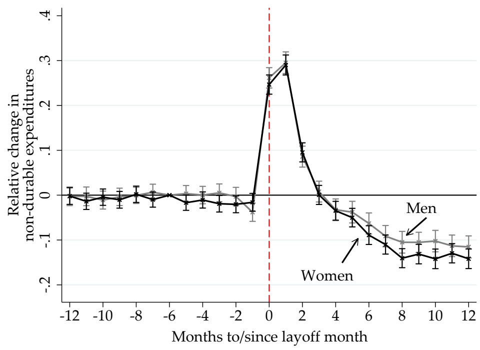
(f) DD estimates for food away from home



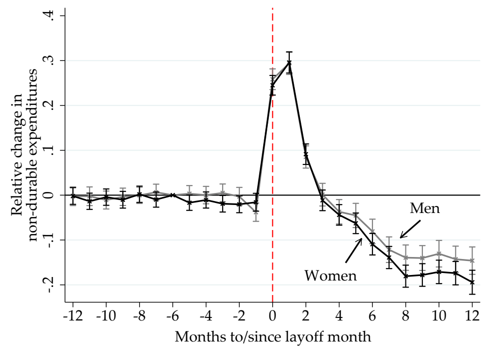
Notes: The figure displays the estimated changes around displacement events for additional expenditure categories, complementing the results in Figure 6. Panel (a) displays the composition of expenditures before layoff (average over $k = -12$ to $k = -6$) in the control group. It is very similar to the treatment group in Figure 6a. Panels (b)-(f) present DD estimates as in Figure 4a (point estimates and 95% confidence intervals) for durables, home improvement, pharmacy expenditures, groceries and food away from home, separately. Panel (b) shows a large increase in spending at layoff and a large long-run loss for durables. However, durables are a not driving the results for total expenditures: non-durables are the main spending category in absolute terms and level changes (see text for details). Panel (c) shows that home improvement expenditures, a category for which complementarities with leisure may be important, is the only category for which estimates for the survival sample are always higher than estimates for the unconditional sample. The evidence for pharmacy expenditures in panel (d) indicates that the long-term loss can be substantial even for categories that are purchased almost exclusively in formal firms. Estimates for groceries in panel (e) are similar to the estimates for food as a whole in Figure 6e. The patterns for food away from home in panel (f) are different from those for all other categories: there is no spike in spending at layoff. However, this category is highly complementary to work. Therefore, the effect of the negative employment shock at layoff might dominate the effect of the increase in cash-on-hand. Moreover, workers could substitute food away by food at home after layoff.

Figure A7. : Heterogeneity results by gender

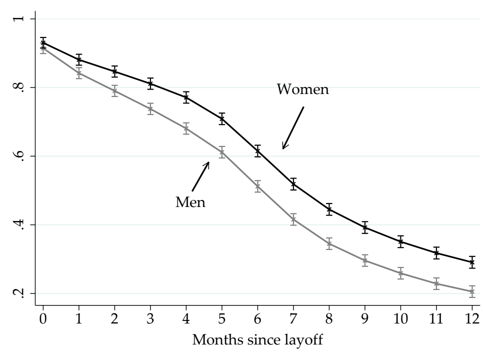
(a) DD estimates for non-durables: women vs. men (using the unconditional sample)



(b) DD estimates for non-durables: women vs. men (using the survival sample)



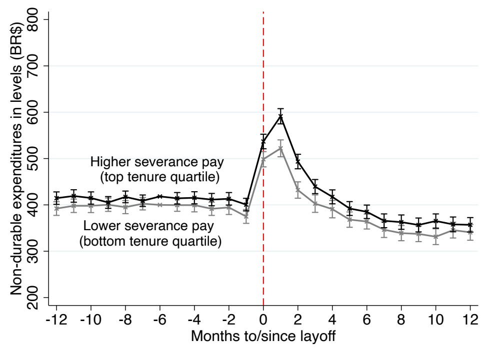
(c) Estimated survival rates in non-employment for women vs. men



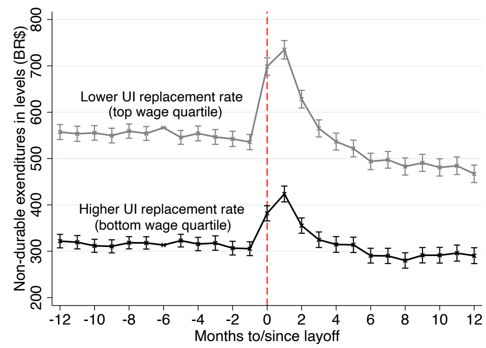
Notes: The figure displays DD estimates as in Figure 6b (point estimates and 95% confidence intervals) for women and men, separately. Panels (a) and (b) presents results for the unconditional and the survival samples, respectively. Panel (c) also displays the estimated survival rates in non-employment for women and men, separately.

Figure A8. : Additional heterogeneity results complementing those in Figure 7

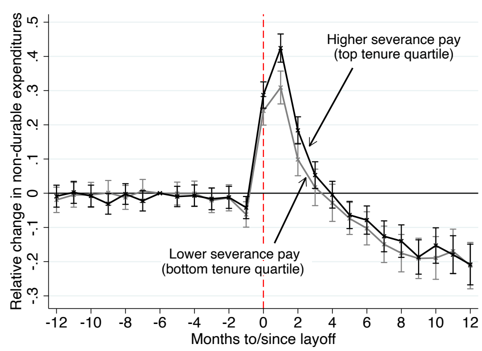
(a) Estimated expenditure levels for non-durables: bottom vs. top tenure quartile (using the unconditional sample)



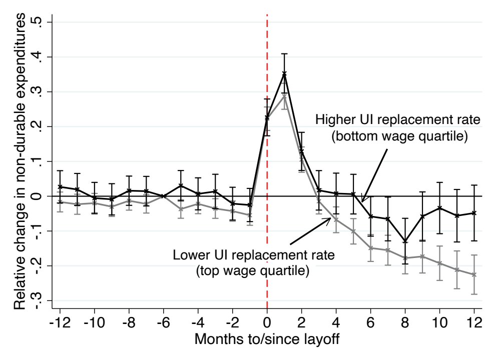
(b) Estimated expenditure levels for non-durables: bottom vs. top wage quartile (using the unconditional sample)



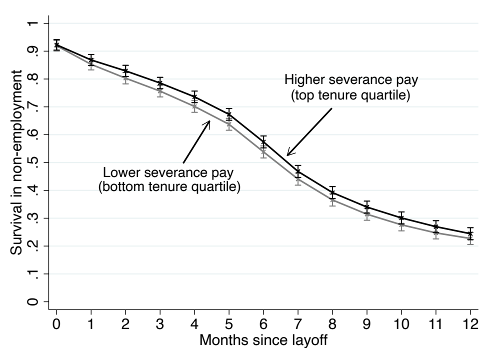
(c) DD estimates for non-durables: bottom vs. top tenure quartile (using the survival sample)



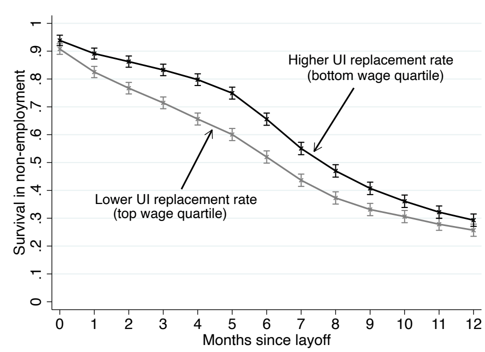
(d) DD estimates for non-durables: bottom vs. top wage quartile (using the survival sample)



(e) Estimated survival rates in non-employment for the bottom vs. top tenure quartile



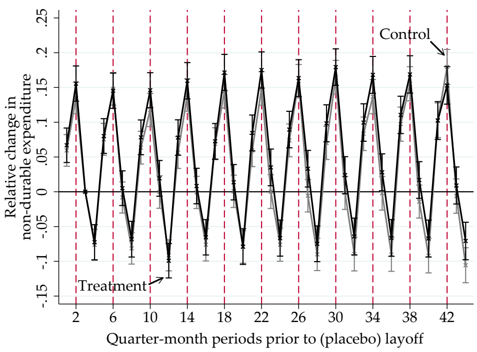
(f) Estimated survival rates in non-employment for the bottom vs. top wage quartile



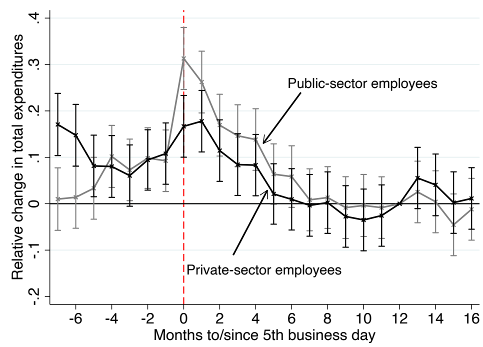
Notes: The figure presents results complementing the evidence in Figure 7. Panels (a) and (b) displays the results in Figure 7 (point estimates and 95% confidence intervals) in terms of the underlying expenditures *levels*. These panels show that workers in the bottom and top tenure quartiles are comparable in terms of average consumption levels prior to layoff (controlling for wages). In contrast, workers in the bottom and top wage quartiles are very different in terms of average consumption levels prior to layoff (even controlling for tenure). Panels (c) and (d) display similar results as in Figure 7 using the survival sample. Panels (e) and (f) display the estimated survival rates in non-employment for the four groups of workers used in Figures 7a and 7b, respectively. In both cases, we estimate event time fixed effects interacted with the relevant quartiles, as well as interacted with the same third-order polynomials in wages or tenure.

Figure A9. : Expenditure profile around paydays when employed

(a) Using our treatment and control groups in the months prior to layoff



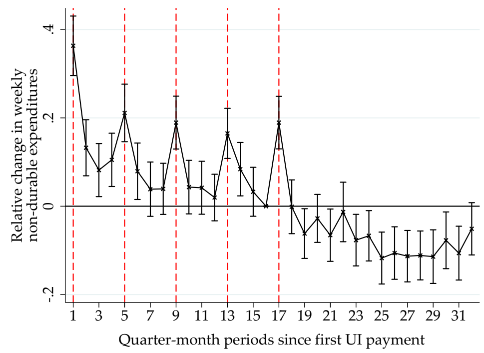
(b) Using all formal employees in our data



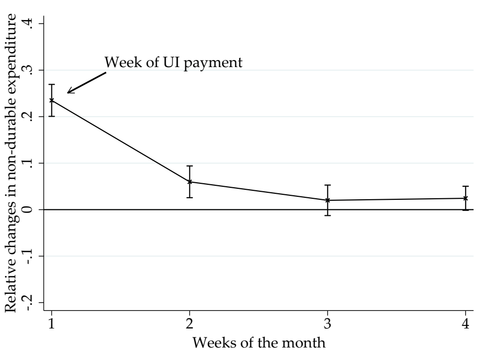
Notes: The figure complements the evidence in Figure 8a by showing that expenditures are also very sensitive to the timing of paydays for formal employees in our data. We use the fact that monthly salaries must be paid before the fifth business day of each month in Brazil. Panel (a) follows a similar approach as in Figures 8a using our treatment and control groups in the months prior to (placebo) layoff (month -12 to -2). We divide each month into 4 quarter-month periods: a first time period including the days before the fifth business day of the month; two 7-day periods (the first one identified by a vertical line starts on the fifth business day); and a fourth period including all the remaining days of the month. We then average expenditures by worker-event and time period and we present the results (point estimates and 95% confidence intervals) of separate analyses for the treatment and control groups (period 3 is the reference period; outcome variables are not de-trended but the specification includes month fixed effects). Non-durable expenditures are about 17% higher in the 7 days following the fifth business day of the month compared to later in the month. Expenditure levels are already higher in the days prior to the fifth business day because many firms pay workers before the 5th business day of the month. Panel (b) uses a much larger dataset including all months in which a worker is observed formally employed in our data, in order to present results at the daily level. We include all months for which we observe 7 days before and 21 days after (and including) the fifth business day of the month (day 0). We present the results of separate event analyses for public-sector and private-sector employees because many public administrations pay their employees exactly on the fifth business day of the month. Accordingly, the decrease in expenditure levels in the 21 days following the fifth business day of the month (the last day is the reference period) is steeper for public employees: a reduction of 40% compared to 20% for private-sector employees. The increase on the fifth business day compared to earlier days is also steeper for public-sector employees.

Figure A10. : Additional results complementing those in Figure 8a

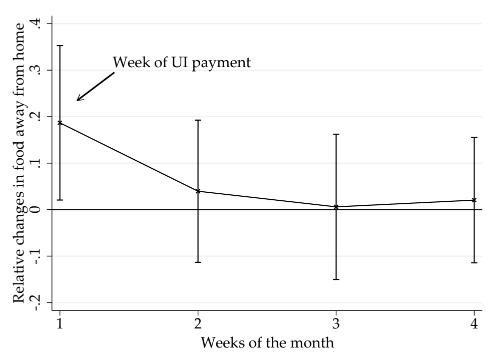
(a) Non-durable spending around UI payday within a month (workers remaining without a job)



(b) Non-durables spending by week (quarter-month period) since UI payday



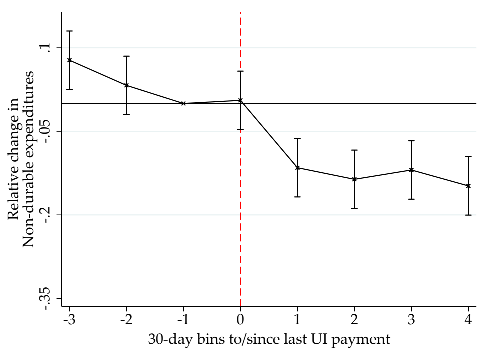
(c) Food away from home spending by week (quarter-month period) since UI payday



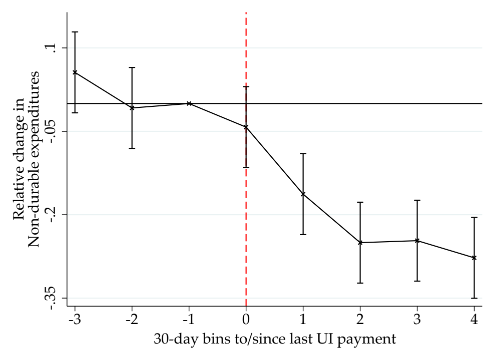
Note: The figure displays robustness checks for the results in Figure 8a. Panel (a) replicates Figure 8a but for the sample of UI exhaustees remaining without a job until the end of the analysis window. In panels (b) and (c), we focus on the 5 UI payment months – periods 1 to 20 in panel (a) – and test whether expenditure levels are systematically different in the 4 different periods – i.e., weeks – within a month. The coefficient for week 1 – the UI payment week – in panel (b) is a linear combination of the coefficients for periods 1, 5, 9, 13 and 17 in Figure 8a; the coefficient for week 2 is a linear combination of the coefficients for periods 2, 6, 10, 14, and 18 in Figure 8a; etc. Panel (c) replicates the same exercise but for spending on food away from home. Even though the estimates for food away from home are less precise, the point estimates are very similar between panels (b) and (c). They imply that spending on food away from home are about 20% higher in the week following a UI payment.

Figure A11. : Robustness checks for Figure 8b – Median regressions

(a) Around the month of UI exhaustion (median; UI exhaustees)



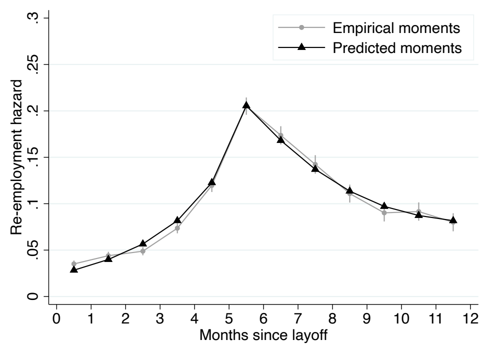
(b) Around the month of UI exhaustion (median; UI exhaustees who remain without a job)



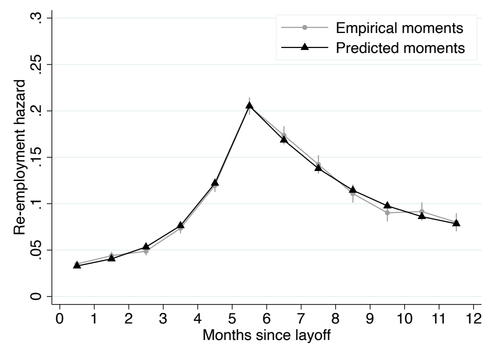
Note: The figure displays robustness checks for the results in Figure 8b. It presents relative change in non-durable expenditures for the median (point estimates and 95% confidence intervals). The point estimates are larger than in Figures 8b, but the overall patterns remain identical: consumption levels are flat before UI exhaustion, but they drop rapidly after UI exhaustion.

Figure A12. : Model fit for the hazard rates of reemployment

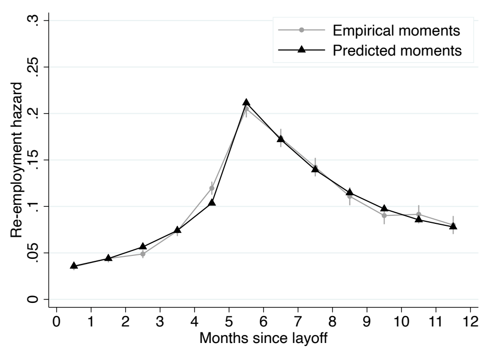
(a) Benchmark: $\delta = .995, \beta = 1$



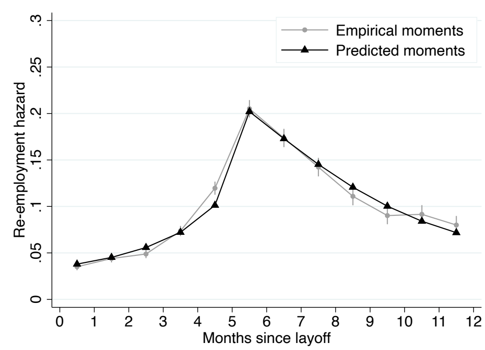
(b) Myopia: $\widehat{\delta} = .69, \beta = 1$



(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .44$



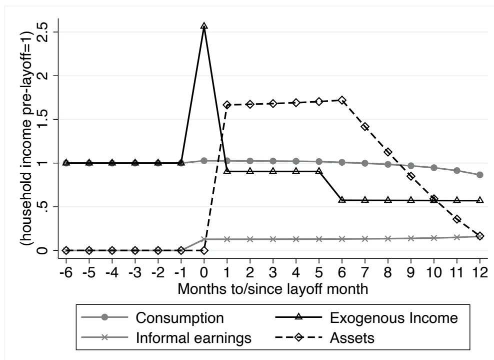
(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .70$



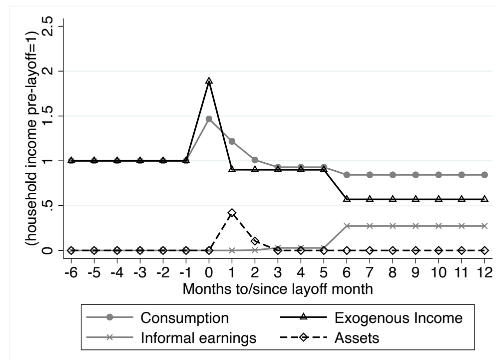
Notes: The figure displays the fit of the four models in Table 2 with respect to the target empirical moments capturing key reemployment patterns in our data. The grey lines display the target empirical moments in each panel. We note that the hazard rate does not decrease between month 0 and 1, a pattern that is driven by workers who do not take up UI in Figure 2c. The black lines display the predicted moments for the estimated models.

Figure A13. : Income, consumption, and asset paths (low search-cost type)

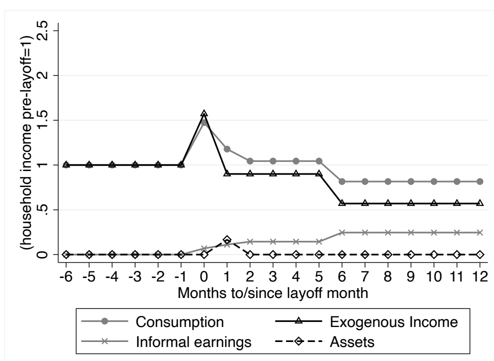
(a) Benchmark: $\delta = .995, \beta = 1$



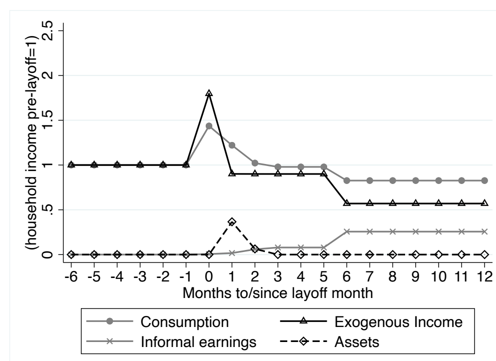
(b) Myopia: $\widehat{\delta} = .69, \beta = 1$



(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .44$



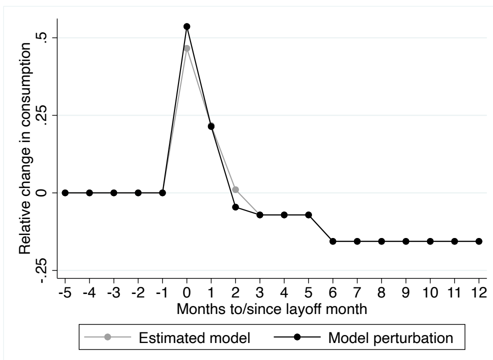
(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .70$



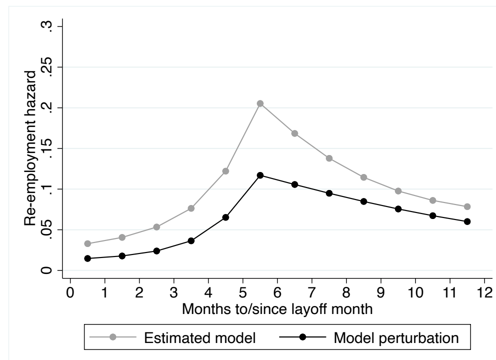
Notes: The figure compares the evolution of exogenous income (wage + income from other household members + UI + SP), consumption, asset, and endogenous income (e.g., informal labor) in each month before and after layoff, as predicted by the four models in Table 2. The figure shows the patterns for the lower search-cost type; the points we make with this figure hold for the higher search-cost type as well. In all four models, the consumer is never hand-to-mouth in month 0 after layoff: the consumer always saves part of the lump-sum severance pay received at layoff. The figure also illustrates the role of the parameter ω, i.e., the share of the lump-sum amount used for consumption purposes in the model. In Table 2, we estimate $\omega = 1$ for the "benchmark" (fixed δ) model and $\omega = 0.5 - 0.66$ for the other models. This is why the level of exogenous income at layoff is much higher in panel (a) than in panels (b)-(d). Thus, for the impatient consumers, the values of $\omega < 1$ allow us to scale down the cash-on-hand in month 0. Otherwise, consumption would be much higher at layoff or would not become flat starting in month 3 after layoff. For the benchmark patient consumer, we have $\omega = 1$ (corner solution) because the model needs omega as high as possible to get as much consumption as possible after layoff.

Figure A14. : Impact on simulated moments from 10% reduction in each estimated parameter value for the myopia model (I)

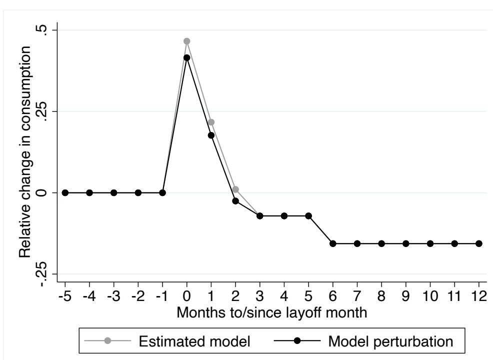
(a) Impact on consumption: $\Delta^{-}\delta$



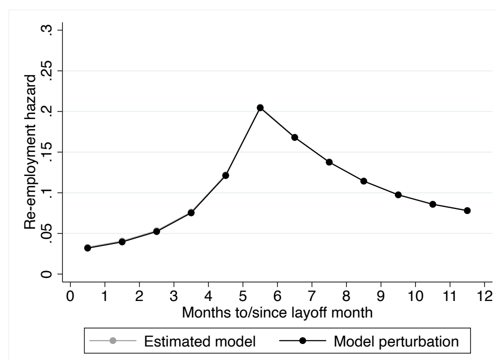
(b) Impact on re-employment hazard: $\Delta^{-}\delta$



(c) Impact on consumption: $\Delta^{-}\omega$



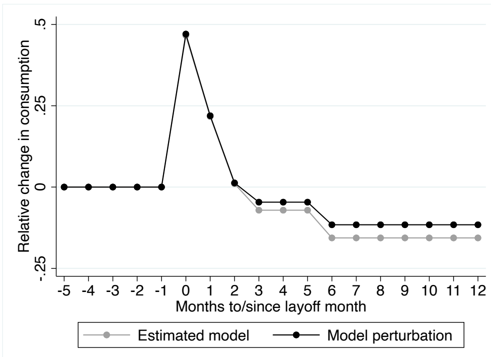
(d) Impact on re-employment hazard: $\Delta^{-}\omega$



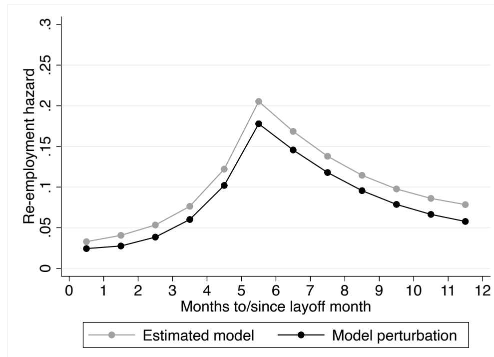
Notes: The figure displays how the predicted consumption profiles (left panels) and re-employment hazard rates (right panels) for the estimated myopia model in column (2) of Table 2 change following a 10% reduction in the value of δ (panels a and b) or ω (panels c and d). We only change one parameter value at the time; the other parameters are fixed at their estimated values in Table 2. Changing δ changes the *shape* of the increase in consumption in the first few months after layoff: reducing δ, thus making the consumer more impatient, increases consumption in month 0, makes the slope of the decrease in consumption afterwards steeper, and ends up reducing consumption in month 2. The higher degree of myopia also reduces search, shifting down the hazard rates. Changing ω only affects how much is consumed before the consumer becomes hand-to-mouth, what we refer to as the "height" of the increase in consumption at layoff in the paper. Consumption decreases in months 0-2 if we reduce the value of ω; it would have increased in those months if we had increased the value of ω instead. Reducing ω increases hazard rates early in the non-employment spell, but only to a small degree, which is not easily seen on the graph: income effects early in the non-employment spell are limited given the size of the increase in cash-on-hand at layoff and the coefficient of risk aversion used in the paper ($\gamma = 2$).

Figure A15. : Impact on simulated moments from 10% reduction in each estimated parameter value for the myopic model (II)

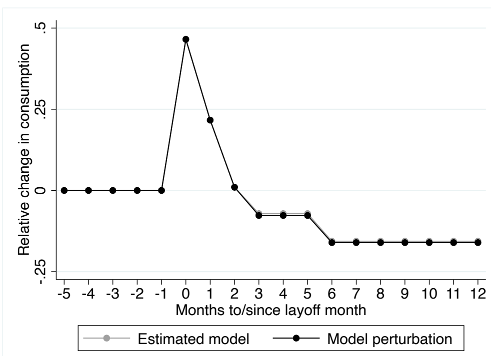
(a) Impact on consumption: $\Delta^{-}\chi$



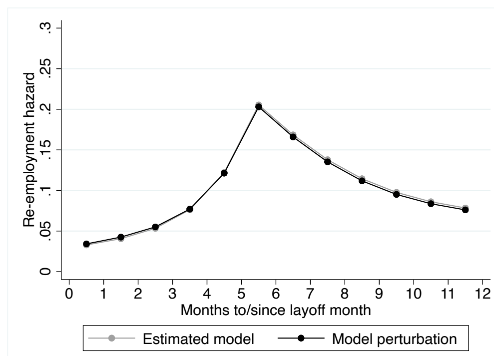
(b) Impact on re-employment hazard: $\Delta^{-}\chi$



(c) Impact on consumption: $\Delta^{-}\lambda$



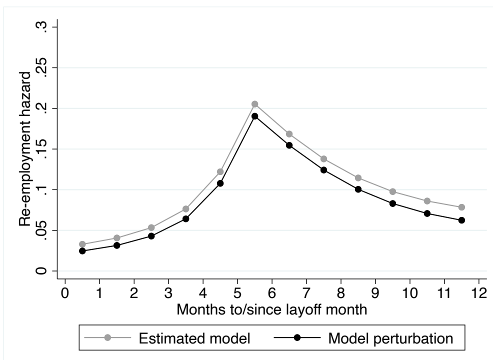
(d) Impact on re-employment hazard: $\Delta^{-}\lambda$



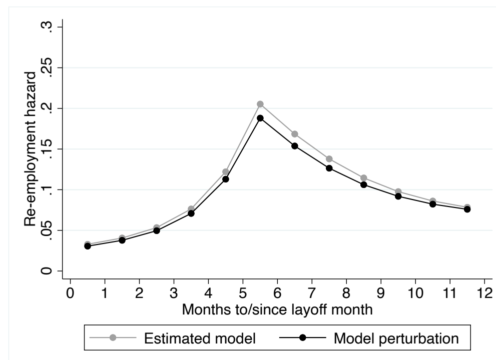
Notes: The figure displays how the predicted consumption profiles (left panels) and re-employment hazard rates (right panels) for the estimated myopia model in column (2) of Table 2 change following a 10% reduction in the value of χ (panels a and b) or λ (panels c and d). We only change one parameter value at the time; the other parameters are fixed at their estimated values in Table 2. Reducing χ, thus lowering the cost of generating additional income (e.g., informal work), does not change consumption in months 0-2 when consumption levels are already very high, but increases consumption levels afterwards. Lowering the cost of generating additional income also reduces job-search efforts. Reducing the inverse of the elasticity of informal work λ slightly shifts down the predicted consumption levels in months 2-5 and to a lower extent afterwards, thus slightly decreasing the size of the drop in consumption at UI exhaustion. It also shifts down the predicted re-employment hazard after month 5. The impacts of reducing the value of λ are limited, however, and not easily seen on the graphs.

Figure A16. : Impact on simulated moments from 10% reduction in each estimated parameter value for the myopic model (III)

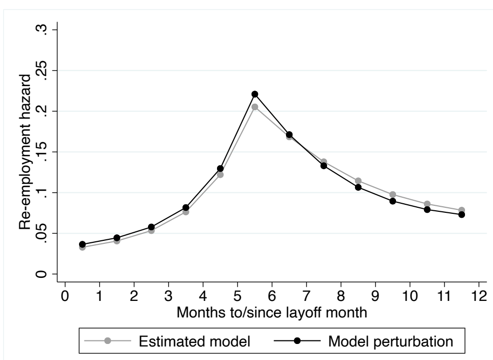
(a) Impact on re-employment hazard: $\Delta^{-}\theta$



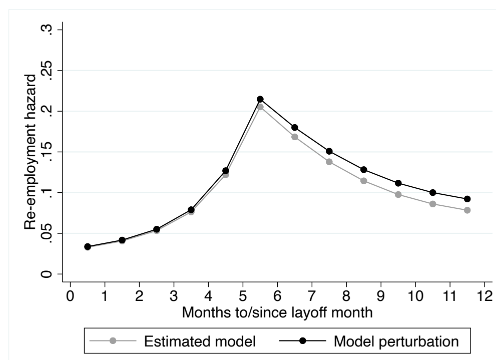
(b) Impact on re-employment hazard: $\Delta^{-}s_0$



(c) Impact on re-employment hazard: $\Delta^{-}\kappa_0$



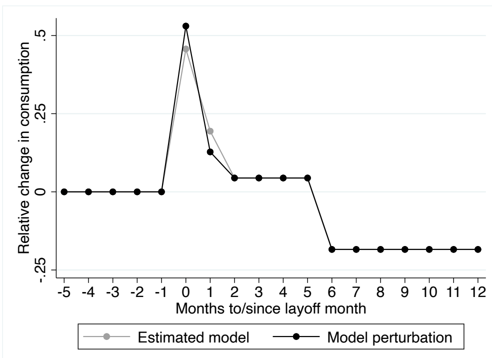
(d) Impact on re-employment hazard: $\Delta^{-}\kappa_1$



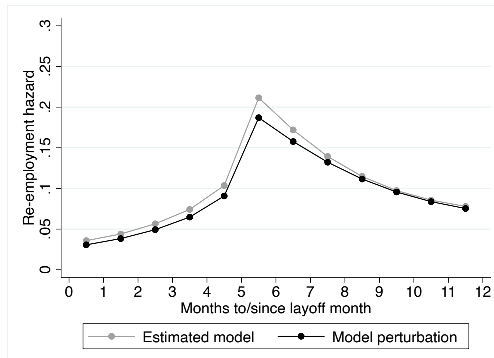
Notes: The figure displays how the re-employment hazard rates for the estimated myopia model in column (2) of Table 2 change following a 10% reduction in the value of θ, s_0, κ_0, and κ_1. We only change one parameter value at the time; the other parameters are fixed at their estimated values in Table 2. The different panels show clearly that these four parameters affect the profile of the hazard rates of reemployment in a very different way. In panel (a), reducing θ shifts the hazard rate down in all periods. In panel (b), a smaller share of low-cost types reduces the re-employment hazard, particularly around UI exhaustion between months 5 and 8. Panel (c) shows that the hazard rate becomes steeper with a reduction in the search cost for the lower-cost type: higher before month 6 and lower after month 7. Panel (d) shows that the hazard rate becomes higher after month 5 with a reduction in the search cost for the higher-cost type. We do not display the effect on consumption profiles because they are barely affected by these changes in reemployment probabilities. This can be seen in Figure A25, in which we show that consumption levels while non-employed are essentially the same for workers with very different reemployment probabilities: those reemployed in month 4 (most of them being of the low-cost type) and those not re-employed by month 12 (most of them being of the high-cost type).

Figure A17. : Impact on simulated moments from 10% reduction in the estimated $\widehat{\beta}$ for the $\beta\delta$ models

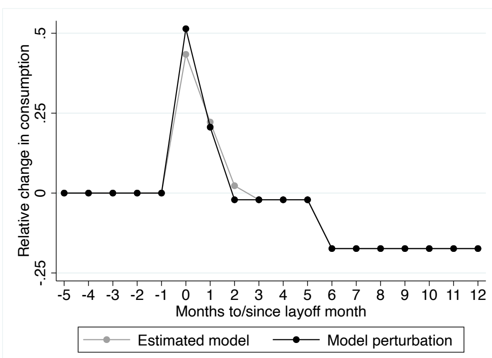
(a) Naïve $\beta\delta$: impact on consumption



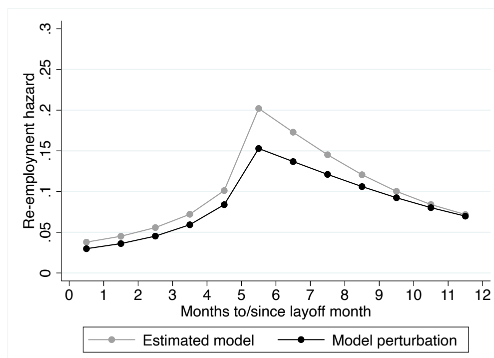
(b) Naïve $\beta\delta$: impact on re-employment hazard



(c) Sophisticated $\beta\delta$: impact on consumption

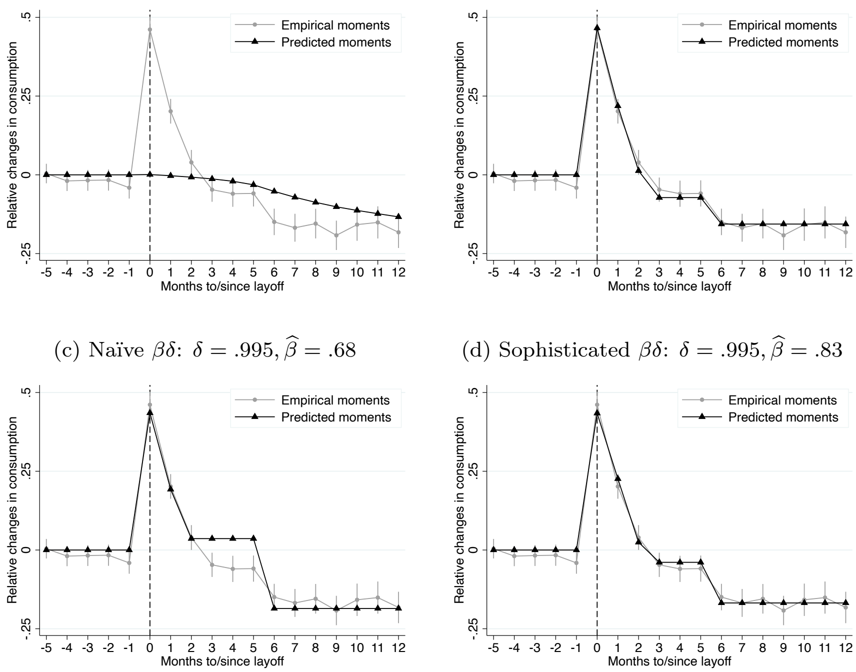


(d) Sophisticated $\beta\delta$: impact on re-employment hazard



Notes: The figure displays how the predicted consumption profiles (left panels) and re-employment hazard rates (right panels) for the estimated naïve and sophisticated present-bias models in columns (3) and (4) of Table 2 change following a 10% reduction in the value of β. We only change one parameter value at the time; the other parameters are fixed at their estimated values in Table 2. We do not display the results from similar exercises for the other parameters in these models because these parameters are shared with the myopia model and so behave similarly as in Figures A14-A16. Changing β changes the *shape* of the increase in consumption in the first few months after layoff: reducing β, thus making the consumer more present-biased, increases consumption in month 0, makes the slope of the decrease in consumption afterwards steeper, and ends up reducing consumption in months 1 and 2. The higher degree of present-bias also reduces search, shifting down the hazard rates, particularly around UI exhaustion between months 5 and 8.

Figure A18. : Model fit using log utility for the consumption profile



(a) Benchmark: $\delta = .995, \beta = 1$

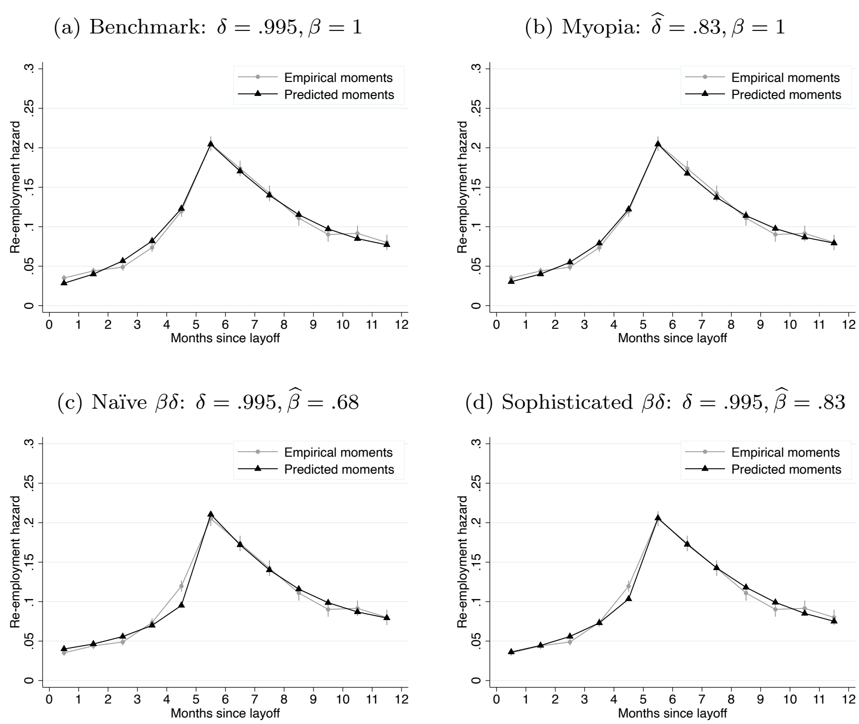
(b) Myopia: $\widehat{\delta} = .83, \beta = 1$

(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .68$

(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .83$

Notes: The figure displays the fit of the four models in Table A1, for which we use log utility ($\gamma = 1$), with respect to the target empirical moments capturing key consumption patterns in our data. The grey lines display the target empirical moments in each panel. The black lines display the predicted moments for the estimated models. These results complement the graphs in Figure 9 in which we display similar results with $\gamma = 2$.

Figure A19. : Model fit using log utility for the hazard rates of reemployment



(a) Benchmark: $\delta = .995, \beta = 1$

(b) Myopia: $\widehat{\delta} = .83, \beta = 1$

(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .68$

(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .83$

Notes: The figure displays the fit of the four models in Table A1, for which we use log utility ($\gamma = 1$), with respect to the target empirical moments capturing key reemployment patterns in our data. The grey lines display the target empirical moments in each panel. The black lines display the predicted moments for the estimated models. These results complement the graphs in Figure A12 in which we display similar results with $\gamma = 2$.

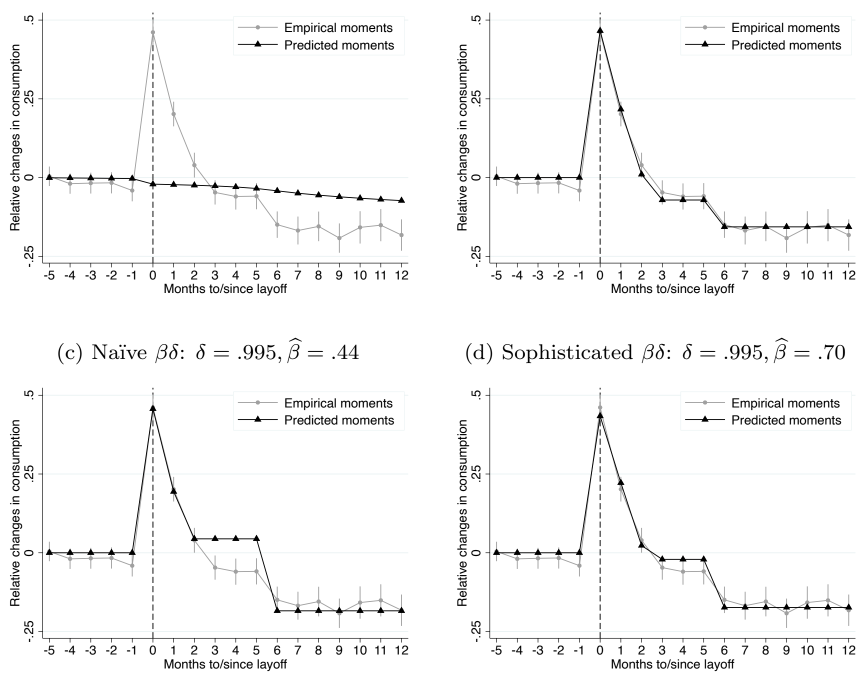
Figure A20. : Predicted consumption profile using the estimated models in Table 2 but assuming positive initial asset ($a_0 = 2$)

(a) Benchmark: $\delta = .995, \beta = 1$

(b) Myopia: $\hat{\delta} = .69, \beta = 1$

(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .44$

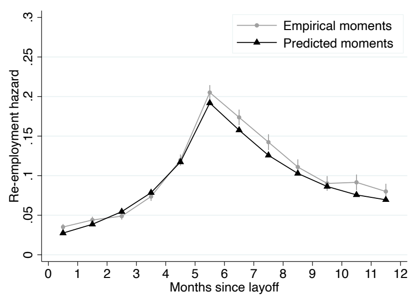
(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .70$



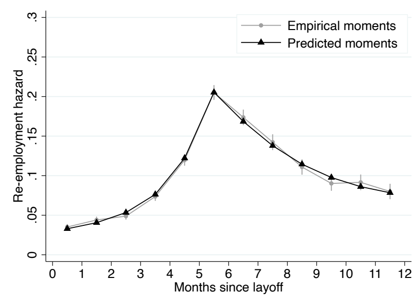
Notes: The figure displays the predicted consumption profile with the four estimated models, using the estimated parameters in Table 2, if we assume a positive initial asset level ($a_0 = 2$ or twice the monthly household income prior to layoff) rather than the zero initial asset assumption used for the estimations ($a_0 = 0$). For reference, the figure also displays the corresponding target empirical moments. The consumption profiles are unchanged compared to those in Figure 9 for the myopia and present-bias models because workers deplete their assets prior to layoff. This is not the case with forward-looking workers, which is why consumption levels remain slightly higher than in Figure 9 for the benchmark model.

Figure A21. : Predicted hazard rates of reemployment using the estimated models in Table 2 but assuming positive initial asset ($a_0 = 2$)

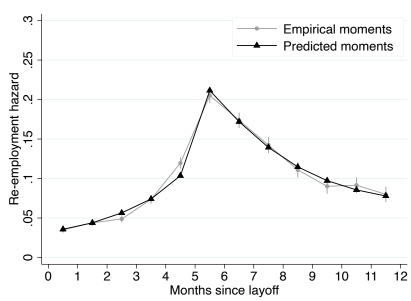
(a) Benchmark: $\delta = .995, \beta = 1$



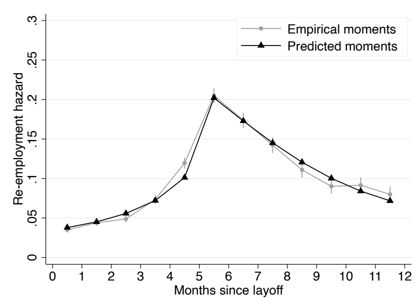
(b) Myopia: $\hat{\delta} = .69, \beta = 1$



(c) Naïve $\beta\delta$: $\delta = .995, \widehat{\beta} = .44$



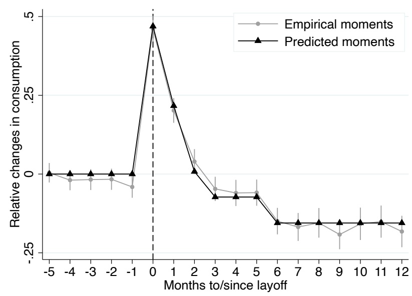
(d) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .70$



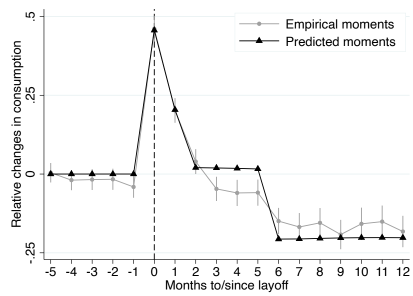
Notes: The figure displays the predicted hazard rates of reemployment with the four estimated models, using the estimated parameters in Table 2, if we assume a positive initial asset level ($a_0 = 2$ or twice the monthly household income prior to layoff) rather than the zero initial asset assumption used for the estimations ($a_0 = 0$). For reference, the figure also displays the corresponding target empirical moments. The hazard rates of reemployment are unchanged compared to those in Figure A12 for the myopia and present-bias models because workers deplete their assets prior to layoff. This is not the case with forward-looking workers, which is why hazard rates remain slightly lower than in Figure A12 for the benchmark model.

Figure A22. : Fit of alternative models for the consumption profile

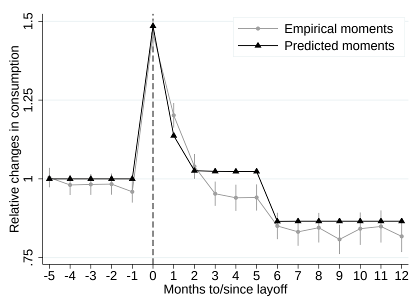
(a) Naïve $\beta\delta$ estimating both β and δ: $\widehat{\delta} = .69, \widehat{\beta} = 1$



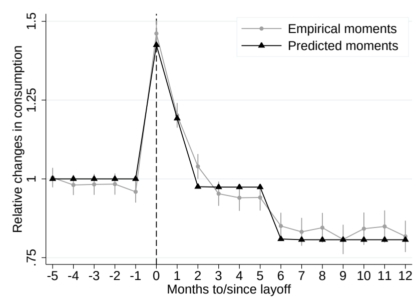
(b) Naïve $\beta\delta$ with heterogeneous β: $\delta = .995, \widehat{\beta_0} = .30, \widehat{\beta_1} = .96$



(c) Naïve $\beta\delta$ for 2-good model: $\delta = .995, \widehat{\beta} = .44$



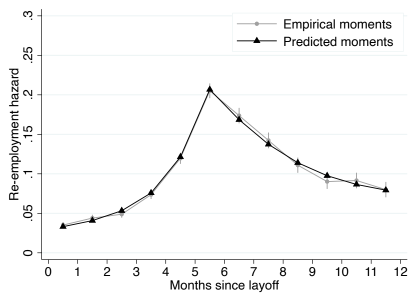
(d) Sophisticated $\beta\delta$ for 2-good model: $\delta = .995, \widehat{\beta} = .73$



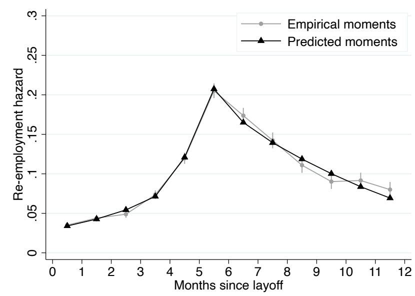
Notes: The figure displays the fit of the four alternative models in Table A3 with respect to the target empirical moments capturing key consumption patterns in our data. The grey lines display the target empirical moments in each panel. The black lines display the predicted moments for the estimated models.

Figure A23. : Fit of alternative models for the hazard rates of reemployment

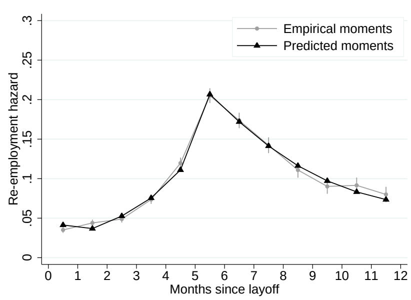
(a) Naïve $\beta\delta$ estimating both β and δ: $\widehat{\delta} = .69, \widehat{\beta} = 1$



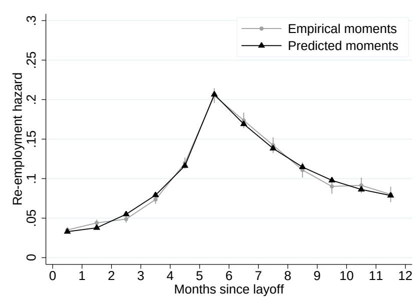
(b) Naïve $\beta\delta$ with heterogeneous β: $\delta = .995, \widehat{\beta_0} = .30, \widehat{\beta_1} = .96$



(c) Naïve $\beta\delta$ for 2-good model: $\delta = .995, \widehat{\beta} = .44$



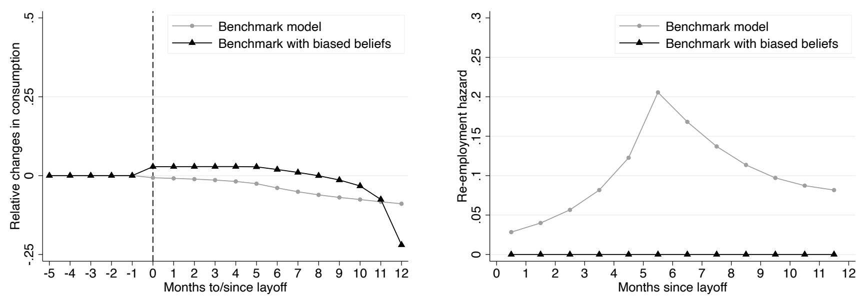
(d) Sophisticated $\beta\delta$ for 2-good model: $\delta = .995, \widehat{\beta} = .73$



Notes: The figure displays the fit of the four alternative models in Table A3 with respect to the target empirical moments capturing key reemployment patterns in our data. The grey lines display the target empirical moments in each panel. The black lines display the predicted moments for the estimated models.

Figure A24. : Predicted consumption profile and hazard rates of reemployment for the benchmark model with and without biased beliefs

(a) Consumption profile (b) Hazard rates of reemployment

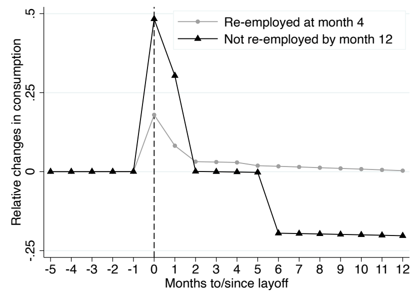


Notes: The figure displays the predicted consumption profile and hazard rates of reemployment if we solve the benchmark model using the estimated parameters in column (1) of Table 2, with and without biased beliefs about future reemployment probabilities. In each panel, the grey lines display the same predicted moments for the benchmark model as in Figures 9a and A12a. The black lines display the predicted moments if we solve the benchmark model, holding the parameters at their values in Table 2, but introducing a *baseline bias* $\overline{h} = .9$ between workers' true and perceived reemployment probabilities (Spinnewijn, 2015).

Figure A25. : Predicted consumption profile by reemployment dates

(a) Sophisticated $\beta\delta$: $\delta = .995, \widehat{\beta} = .70$

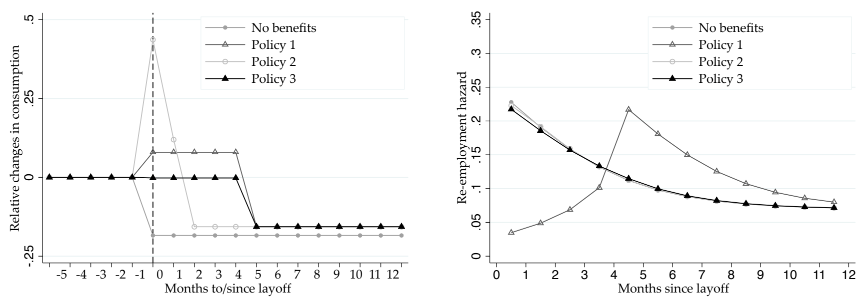
(b) Naïve $\beta\delta$ with heterogeneous β: $\delta = .995, \widehat{\beta_0} = .30, \widehat{\beta_1} = .96$



Notes: The figure displays the predicted consumption profile for workers reemployed in month 4 after layoff vs. for workers not yet reemployed by month 12 after layoff. The predicted consumption profile in panel (a) uses the sophisticated present-bias model in column (4) of Table 2, which assumes no heterogeneity in present bias across workers. The predicted consumption profile in panel (b) uses the naïve present-bias model with two present-bias types in column 2 of Table A3.

Figure A26. : Counterfactual policies using the naïve present-bias model

(a) Consumption profile　　　　(b) Hazard rates of reemployment



	Δ Welfare Insurance Value	Δ Welfare Incentive effect	Δ Welfare Additional
	[1]	[2]	[3]
Policy 1: 5 months of UI	0.14	-0.34	-0.24
Policy 2: equivalent SP paid lump-sum at layoff	-0.06	0.00	-0.01
Policy 3: equivalent SP paid in 5 monthly installme	0.12	0.00	-0.04

Notes: The figure displays the predicted consumption profile, hazard rates of reemployment, and welfare effects for the same counterfactual job displacement insurance designs as in Figure 10, but using the naïve present-bias model in column (3) of Table 2.

Table A1: Estimated parameters for the structural models with log utility ($\gamma = 1$)

	δ-discounting with fixed δ (benchmark)		δ-discounting with free δ (myopia)		βδ-discounting with free β (naïve)		βδ-discounting with free β (sophisticated)	
	[1]		[2]		[3]		[4]	
Parameters								
Discount factor (1 month): δ	0.995	(fixed)	**0.831**	(0.003)	0.995	(fixed)	0.995	(fixed)
Present bias parameter: β	1.000	(fixed)	1.000	(fixed)	**0.685**	(0.003)	**0.838**	(0.002)
Inverse of search elasticity: θ	**0.098**	(0.022)	**0.393**	(0.008)	**0.344**	(0.007)	**0.127**	(0.001)
Search cost (lower-cost type): κ_0	**5.666**	(1.106)	**1.243**	(0.035)	**1.061**	(0.025)	**2.677**	(0.066)
Search cost (higher-cost type): κ_1	**14.158**	(0.951)	**3.022**	(0.145)	**8.518**	(0.373)	**10.704**	(0.281)
Share of lower-cost type: s_0	**0.542**	(0.012)	**0.515**	(0.013)	**0.477**	(0.015)	**0.545**	(0.016)
Share of lump-sum amount for consumption: ω	**1.000**	(0.119)	**0.663**	(0.006)	**0.500**	(0.007)	**0.639**	(0.008)
Informal work cost: χ	**17.949**	(52.397)	**1.251**	(0.010)	**2.194**	(0.080)	**1.371**	(0.019)
Inverse of informal work elasticity: λ	**1.388**	(1.475)	**0.041**	(0.004)	**0.412**	(0.022)	**0.098**	(0.008)
Model fit								
Number of moments used	30		30		30		30	
Number of estimated parameters	7		8		8		8	
Goodness of fit: consumption moments	681.48		17.67		77.66		17.58	
Goodness of fit: search moments	42.09		26.74		73.76		40.15	

Notes: The table displays parameter estimates for the four versions of the structural model described in Section IV.D, but using log utility ($\gamma = 1$). The parameters are estimated by minimizing the distance between the target empirical moments and the same moments as predicted by the models for a given vector of free parameters.

Table A2: Comparison of the Marginal Propensity to Consume (MPC) non-durables out of cash-on-hand in the data and in the estimated models (log utility)

Sources of variation in cash-on-hand	MPC from the data [95% CI]		MPC from models: δ-discounting with fixed δ (benchmark)	δ-discounting with free δ (myopia)	βδ-discounting with free β (naïve)	βδ-discounting with free β (sophisticated)
	[1]		[2]	[3]	[4]	[5]
Layoff event						
Main analysis sample	**0.224**	[0.210; 0.237]	*0.004*	*0.203*	*0.192*	*0.199*
Sample reemployed in month 4	**0.215**	[0.153; 0.278]	*0.031*	*0.203*	*0.192*	*0.199*
Sample not reemployed by month 12	**0.215**	[0.195; 0.236]	*-0.044*	*0.203*	*0.191*	*0.199*
Higher severance pay (SP +58%)	**0.162**	[0.144; 0.180]	*0.024*	*0.216*	*0.182*	*0.195*
Lower severance pay (SP -10%)	**0.31**	[0.255; 0.365]	*-0.004*	*0.194*	*0.196*	*0.195*
Higher UI replacement rate (lower wage)	**0.214**	[0.172; 0.256]	*0.022*	*0.227*	*0.192*	*0.217*
Lower UI replacement rate (higher wage)	**0.128**	[0.110; 0.147]	*-0.021*	*0.165*	*0.158*	*0.166*
UI exhaustion event	**0.228**	[0.182; 0.275]	*0.065*	*0.097*	*0.266*	*0.152*
Firing event	**0.175**	[0.091; 0.259]	*0.254*	*0.146*	*0.173*	*0.156*

Notes: The table compares estimates of MPCs from the empirical analysis to similar MPCs as predicted by the estimated models in Table A1 (using log utility or $\gamma = 1$). Column (1) displays estimates of the marginal propensity to spend on non-durables (with their 95% confidence interval) based on different sources of variations in the data. Columns (2)-(5) present MPCs based on similar sources of variation in cash-on-hand, as predicted by each of the four models, respectively. For the sake of comparability, the model-based MPCs are scaled by the share of non-durables out of total household expenditures in the POF survey data (0.401).

Table A3: Estimated parameters for alternative structural models

	βδ-discounting with free β and δ (naïve)		βδ-discounting with free heterogenous β (naïve)		βδ-discounting with free β for 2-good model (naïve)		βδ-discounting with free β for 2-good model (sophisticated)	
	[1]		[2]		[3]		[4]	
Parameters								
Discount factor (1 month): δ	**0.687**	(0.015)	0.995	(fixed)	0.995	(fixed)	0.995	(fixed)
Present bias parameter: β	**1.000**	(0.032)			**0.444**	(0.004)	**0.729**	(0.019)
Present bias parameter (lower-beta type): β_0			**0.301**	(0.004)				
Present bias parameter (higher-beta type): β_1			**0.958**	(0.008)				
Share of lower-beta type: h_0			**0.602**	(0.004)				
Inverse of search elasticity: θ	**0.619**	(0.019)	**0.326**	(0.008)	**1.028**	(0.018)	**0.336**	(0.019)
Search cost (lower-cost type): κ_0	**0.620**	(0.026)	**0.296**	(0.005)	**1.358**	(0.050)	**2.767**	(0.141)
Search cost (higher-cost type): κ_1	**1.975**	(0.134)	**25.976**	(7.192)	**48.108**	(4.244)	**14.507**	(0.507)
Share of lower-cost type: s_0	**0.515**	(0.012)	**0.731**	(0.023)	**0.523**	(0.018)	**0.488**	(0.015)
Share of lump-sum amount for consumption: ω	**0.661**	(0.006)	**0.726**	(0.008)	1.000	(fixed)	1.000	(fixed)
Curvature of utility over good 2 vs. good 1: α					**0.361**	(0.005)	**0.383**	(0.006)
Informal work cost: χ	**1.555**	(0.018)	**17.517**	(2.483)	**48.222**	(16.376)	**7.077**	(2.205)
Inverse of informal work elasticity: λ	**0.080**	(0.005)	**1.424**	(0.058)	**1.990**	(0.167)	**0.574**	(0.129)
Model fit								
Number of moments used	30		30		30		30	
Number of estimated parameters	9		10		8		8	
Goodness of fit: consumption moments	18.72		69.32		79.28		40.86	
Goodness of fit: search moments	13.65		25.32		40.28		27.34	

Notes: The table displays parameter estimates for the four alternative models discussed in Sections IV.D and IV.F. The parameters are estimated by minimizing the distance between the target empirical moments and the same moments as predicted by the models for a given vector of free parameters.

Table A4: Comparison of the Marginal Propensity to Consume (MPC) non-durables out of cash-on-hand in the data and in the alternative models

Sources of variation in cash-on-hand	MPC from the data [95% CI]		MPC from models: βδ-discounting with free β and δ (naïve)	βδ-discounting with free heterogenous β (naïve)	βδ-discounting with free β for 2-good model (naïve)	βδ-discounting with free β for 2-good model (sophisticated)
	[1]		[2]	[3]	[4]	[5]
Layoff event						
Main analysis sample	**0.224**	[0.210; 0.237]	*0.202*	*0.201*	*0.188*	*0.173*
Sample reemployed in month 4	**0.215**	[0.153; 0.278]	*0.202*	*0.085*	*0.187*	*0.173*
Sample not reemployed by month 12	**0.215**	[0.195; 0.236]	*0.202*	*0.227*	*0.190*	*0.173*
Higher severance pay (SP +58%)	**0.162**	[0.144; 0.180]	*0.216*	*0.201*	*0.160*	*0.151*
Lower severance pay (SP -10%)	**0.31**	[0.255; 0.365]	*0.193*	*0.205*	*0.194*	*0.174*
Higher UI replacement rate (lower wage)	**0.214**	[0.172; 0.256]	*0.250*	*0.212*	*0.260*	*0.242*
Lower UI replacement rate (higher wage)	**0.128**	[0.110; 0.147]	*0.148*	*0.158*	*0.099*	*0.080*
UI exhaustion event	**0.228**	[0.182; 0.275]	*0.095*	*0.270*	*0.191*	*0.200*
Firing event	**0.175**	[0.091; 0.259]	*0.145*	*0.209*	*0.126*	*0.178*

Notes: The table compares estimates of MPCs from the empirical analysis to similar MPCs as predicted by the alternative models in Table A3. Column (1) displays estimates of the marginal propensity to spend on non-durables (with their 95% confidence interval) based on different sources of variations in the data. Columns (2)-(5) present MPCs based on similar sources of variation in cash-on-hand, as predicted by each of the four models, respectively. For the sake of comparability, the model-based MPCs are scaled by the share of non-durables out of total household expenditures in the POF survey data (0.401) in columns (2) and (3). This is not necessary in columns (4) and (5) because the model estimation enforces that non-durables account for .401 of total consumption before layoff (the MPC presented in these columns is the marginal propensity to consume good c_1).

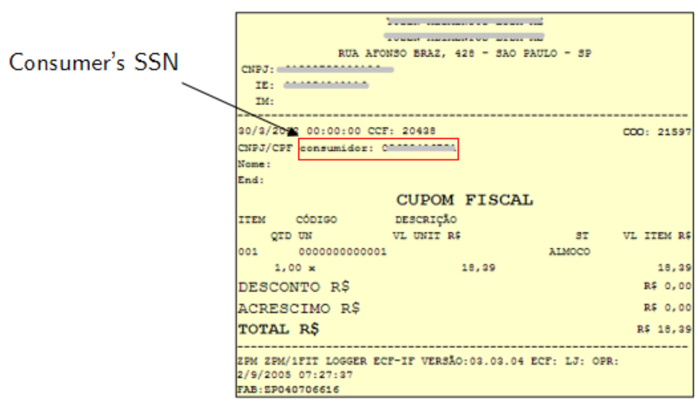
Online Appendix B - Spending Categorization

This appendix provides details on the spending categorization of the de-identified receipts data. It also describes the steps taken to compare the data in our paper with a Household Survey data from the Brazilian Census Bureau (IBGE), the Pesquisa de Orçamentos Familiares (POF) of 2008/2009.

B.1. Categorization of Receipts into Spending

The receipts data contains information about the total value of the receipt, the merchant and a time stamp. The time recorded in the receipt allows us to create a weekly and monthly panel of spending used in the paper. Figure B1 shows an example of a receipt from a purchase in a São Paulo grocery shop. All receipts have a field to fill in the buyer's tax ID number (CNPJ or CPF as indicated in the figure) if provided. In business-to-business transactions, the tax ID is the CNPJ of the firm, and the receipt may be used as tax credit in the VAT system by the buying firm. In sales to final consumers, consumers' ID number (their CPF) can be indicated in this field as highlighted in Figure B1, in which case they are eligible for lottery tickets and tax rebates (see more details in Naritomi 2019).

Figure B1: Receipt from São Paulo



Notes: This picture shows the receipt typically issued by retail firms. All receipts have a field to fill in the buyer's tax ID number (CNPJ or CPF as indicated in the figure) if provided. In business-to-business transactions, the tax ID is the CNPJ, and the receipt may be used as tax credit in the VAT system by the buying firm. In sales to final consumers, consumers' ID number (their CPF) can be indicated in this field as highlighted in the picture. This specific receipt is a real receipt that was requested by the researchers at a retail establishment in São Paulo.

In order to categorize the data from receipts into different types of spending, we use the sector of activity of the establishment that issued the receipt as defined by the National Classification of Economic Activities - Classificação Nacional de Atividades Econômicas (CNAE) version 2.0. More precisely, we use the most dis-aggregated classification, which is a 7-digit sector definition that allows us to finely categorize the type of shop consumers are buying from. For instance: 47 is Retail; 472 is Retail of food, beverages, tobacco; 4722-9 is Retail of meat and fish; 4722-9/01 is Retail of meat.

The two main categories that we would like to analyze separately are durables and non-durables. For this categorization, we followed the North American Industry Classification System (NAICS) from the U.S. Bureau of Labor Statistics (LBS). Two research assistants worked on this categorization separately to ensure consistency using the description of the CNAE codes, and a third one reviewed the final list. For instance, we classified as *durables* purchases 7-digit CNAE codes that have descriptions similar to the goods described in NAICS 423 ("Durable Goods"). It includes mostly personal electronics, home appliances, furniture, vehicles and vehicle parts.

We classified as *non-durables* purchases all CNAE codes that are associated with goods described in NAICS 424 ("Nondurable Goods"), but we include transportation fuel (mostly gasoline or other fuel for auto-vehicles) in order to make our non-durable classification comparable to Lusardi (1996) and Ganong and Noel (2019).[1]. We also created a separate category of spending from durables and non-durables: *home improvement*. It includes expenditures related to building materials, renovations and construction work. These are expenditures that could be considered complements to having more disposable time after layoff, and are related to construction work and purchases of tools that could be used in such activities.

Table B1 and B2 list the CNAE codes for each category we analyze in Figure 6 and Figure A6. In total, we observe 988 CNAE codes in the data. However, the purchases are highly concentrated among fewer CNAE codes. We restrict attention to CNAE codes that together amount to 95% of the receipts in each category. Table B1 shows the main CNAE codes and their description for Durables and Non-Durables. Within non-durables, we highlight the CNAE codes in *Strict non-durables* and *Other non-durables*. CNAE codes categorized as *Strict non-durables* are non-durable categories that follow the definition proposed by Lusardi (1996): it excludes education related expenses (e.g., bookstores), health-related expenditures (*Pharmaceutical* sectors), and semi-durables (e.g., apparel, toy or pet shops, office supply shops). These categories are listed under *Other non-durables* in the table.

Table B2 shows the CNAE codes and their description for home improvement, pharmacy and food. *Home improvement* CNAE codes with descriptions related to construction materials or tools. *Pharmaceutical* is basically drugstores only

[1]There are also categories for "Other" (about 0.1%), which are CNAE codes that are not easily classified (e.g., labeled as miscellany retail), and "missing" (about 4%), which are cases where the firm ID and/or CNAE code is unknown.

(more than 95% of all receipts in this CNAE). Within food, we highlight the CNAE codes classified as food away from home and groceries, separately. *Food away* from home are CNAE codes with descriptions associated to food sold and typically prepared and consumed outside the home such as restaurants. *Groceries* are CNAE codes with descriptions associated to grocery shops or retail of food (or predominantly food) that is prepared at home.

B.2. Comparison between Spending data from Receipts vs. Survey

In order to check how our consumer spending measure compares with other data sources, we analyze the most recent household expenditure survey (POF) available at IBGE, which is 2008/2009. It collects data on income, household demographic characteristics and expenditures. The survey is representative at the state level, and we restrict attention to households in the state of São Paulo. Food expenditures are collected through diaries, and non-food expenditures are based on recall. Although there are potential concerns about data quality with this type of expenditure data - see, for instance, Lanjouw (2005) - it is a useful external data source to benchmark our data. Below, we describe several steps that were taken to harmonize the two datasets for this comparison.

Harmonizing POF and our consumer spending data

Our consumer spending sample. We pooled together the App de-identified users that were found in the matched employer-employee data (RAIS). In POF, surveys are conducted at different time periods between 2008 and 2009. To make our data compatible with the sampling structure of POF surveys, we drew a random simulated survey month for each worker in 2011, which is the earliest year in our data for which we can measure consumer spending for the previous 12 months (the data start in 2010). We restricted our sample only to individuals who were working in the selected month and who were between 20 and 50 years old. After selecting the hypothetical survey month, we used a window of 12 months of consumption from our data - the survey month and 11 months before - to aggregate the total expenditure. All values are monthly averages for 12 months.

POF survey sample. For the sake of comparison with our consumer spending data, we restrict attention to households with formal workers from São Paulo who were between 20 and 50 years old. Importantly, we need to identify formal labor income in POF as this is the only income source we can observe in RAIS. POF does not identify formal workers directly, but it is possible to define formality as private or public jobs with income subject to compulsory contribution to social security. All expenditure and income values are monthly averages for the 12-month period before (and including) the survey month.

Categorization of expenditures. The POF survey covers a broader set of expenditures compared to our consumer spending data: it includes housing and a larger range of services (e.g., transportation services such as public transport or taxis; these purchases are not taxed by the state VAT). In order to compare similar categories across the two datasets, we categorized the purchases from POF according to the "Descrição do Item" (the product description) in POF's catalog of 6-digit code products. In 2008/2009, the catalog had 13,785 items. Two research assistants categorized the whole catalog separately, and a third research assistant revised the final categories to ensure consistency. Similarly to the CNAE description, the text allows us to classify purchases between categories of interest such as: durables, non-durables, and the other sub-categories described above into which we categorized the CNAE of merchant.

Another relevant difference between the two datasets is that total expenditures in POF are best measured at the household level, whereas our consumer spending data is reported by the individual. The POF survey has expenditure measures at the individual and household levels, but some relevant items are only measured at the household level, such as groceries or durables like home appliances. Thus, we restrict attention to household-level expenditure data in POF. Even though we cannot observe families in our data, it is possible that the expenditures we observe are not individual, but household expenditures. The NFP program creates incentives for households to provide the same ID number when making a purchase independently of the identity of the consumer: it gives participants one lottery ticket for each R$50 in total reported purchases. Indeed, in the survey we conducted in São Paulo, more than 60% of workers indicated that all their household members participated in the NFP program with the same ID number (see Appendix Table C1).

Coverage of our consumer spending data across the formal wage distribution

This section shows how the different consumption measures from the two sources of data behave relatively to formal income changes in a cross-section. Beyond potential data coverage differences, it is possible that, in our data, the consumer may not provide her ID number for all her purchases and the consumer may not be making all the households' purchases. Nonetheless, overall, the empirical regularities in the data show that the coverage of our data is relatively constant when we look at a cross-section of income levels.

We construct three consumer spending measures to compare POF and our data: *(i) Total expenditure*, which is the total household expenditure observed in POF and the total expenditure observed in our data, irrespective of their categories; *(ii) Comparable categories* excludes from the *Total expenditure* in POF the categories that cannot be measured in our data (e.g., housing); *(iii) Total non-durable expenditure* is defined in both datasets as described in Table B1.

Figure B2 displays the same graph as in Figure 3a for each of the three measures of spending. In both datasets, we restrict attention to workers that earn at least one minimum wage, which is the relevant sample for our study.[2] The y-axis displays the ratio of spending in our data to household expenditures in the survey data. We use deciles of the POF formal wage distribution to define bins, and we averaged the spending in each bin for each dataset separately using sampling weights based on a vector of covariates (quartiles of age, and dummy variables for being white, having a high school degree, and being female) such that our sample matches the POF sample on observables.

Figure B2 shows the ratio of this weighted average in the receipt data over the survey data. Standard errors are calculated using the delta method. The x-axis displays the log of the median monthly wage of workers in each bin formally employed at the time of the interview.[3] Importantly, there is no systematic change in expenditure coverage by wage levels, indicating that the coverage of our data is relatively constant across income levels. Also, Figure 3a shows that our data capture a sizable share of households' expenditures: 16% of overall mean consumption (including in the denominator categories we do not observe); 26% of the mean expenditure in the survey data for comparable categories; 34% of mean non-durable expenditures.

[2]All full-time formal workers should earn at least one minimal wage (R$510 in 2010). Some workers are recorded as earning less than one minimum wage despite being formal because they did not work all days of the month. The range of wages in the samples that we study are all above one minimum wage.

[3]We randomly assign a simulated interview date to formal workers in our data (see Appendix B).

Table B1: Cross-walk between main categories of spending and sector of activity (CNAE)

Category		CNAE	CNAE description
Non-Durables	*Strict non-durables*	4639701	Comércio atacadista de produtos alimentícios em geral
		4711301	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - hipermercados
		4711302	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - supermercados
		4712100	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - minimercados, mercearias e armazéns
		4721102	Padaria e confeitaria com predominância de revenda
		4721104	Comércio varejista de doces, balas, bombons e semelhantes
		4722901	Comércio varejista de carnes - açougues
		4729699	Comércio varejista de produtos alimentícios em geral ou especializado em produtos alimentícios não especificados anteriormente
		4731800	Comércio varejista de combustíveis para veículos automotores
		4772500	Comércio varejista de cosméticos, produtos de perfumaria e de higiene pessoal
		5611201	Restaurantes e similares
		5611203	Lanchonetes, casas de chá, de sucos e similares
	Other non-durables	4647801	Comércio atacadista de artigos de escritório e de papelaria
		4693100	Comércio atacadista de mercadorias em geral, sem predominância de alimentos ou de insumos agropecuários
		4713001	Lojas de departamentos ou magazines
		4713002	Lojas de variedades, exceto lojas de departamentos ou magazines
		4755502	Comercio varejista de artigos de armarinho
		4761001	Comércio varejista de livros
		4761003	Comércio varejista de artigos de papelaria
		4763601	Comércio varejista de brinquedos e artigos recreativos
		4771701	Comércio varejista de produtos farmacêuticos, sem manipulação de fórmulas
		4771702	Comércio varejista de produtos farmacêuticos, com manipulação de fórmulas
		4781400	Comércio varejista de artigos do vestuário e acessórios
		4782201	Comércio varejista de calçados
		4789004	Comércio varejista de animais vivos e de artigos e alimentos para animais de estimação
		4789099	Comércio varejista de outros produtos não especificados anteriormente
Durables		2621300	Fabricação de equipamentos de informática
		4511101	Comércio a varejo de automóveis, camionetas e utilitários novos
		4511102	Comércio a varejo de automóveis, camionetas e utilitários usados
		4530701	Comércio por atacado de peças e acessórios novos para veículos automotores
		4530703	Comércio a varejo de peças e acessórios novos para veículos automotores
		4530705	Comércio a varejo de pneumáticos e câmaras-de-ar
		4541203	Comércio a varejo de motocicletas e motonetas novas
		4541205	Comércio a varejo de peças e acessórios para motocicletas e motonetas
		4649401	Comércio atacadista de equipamentos elétricos de uso pessoal e doméstico
		4649499	Comércio atacadista de outros equipamentos e artigos de uso pessoal e doméstico não especificados anteriormente
		4651601	Comércio atacadista de equipamentos de informática
		4732600	Comércio varejista de lubrificantes
		4752100	Comércio varejista especializado de equipamentos de telefonia e comunicação
		4753900	Comércio varejista especializado de eletrodomésticos e equipamentos de áudio e vídeo
		4754701	Comércio varejista de móveis
		4754702	Comércio varejista de artigos de colchoaria
		4754703	Comércio varejista de artigos de iluminação
		4755503	Comercio varejista de artigos de cama, mesa e banho
		4756300	Comércio varejista especializado de instrumentos musicais e acessórios
		4757100	Comércio varejista especializado de peças e acessórios para aparelhos eletroeletrônicos para uso doméstico, exceto informática e comunicação
		4759801	Comércio varejista de artigos de tapeçaria, cortinas e persianas
		4759899	Comércio varejista de outros artigos de uso doméstico não especificados anteriormente
		4763602	Comércio varejista de artigos esportivos
		4763603	Comércio varejista de bicicletas e triciclos; peças e acessórios
		4789002	Comércio varejista de plantas e flores naturais
		6120501	Telefonia móvel celular
		9511800	Reparação e manutenção de computadores e de equipamentos periféricos

Notes: The table lists the cross-walk between the main spending categories used in the paper based on the sector of activity of the shops (CNAE) that issue the receipts. There is a total of 988 7-digit CNAE codes that were classified into different consumption categories based on the description of the sector. The list displayed in the table restricts attention to the top 7-digit CNAE codes in each category in terms of number of receipts that add up to 95% of all receipts in that category. *Durables*: 7-digit CNAE codes with descriptions similar to the goods described in NAICS 423 of U.S. LBS. improvements/works in a home. *Non-durables*: CNAE codes that can be classified following U.S. BLS NAICS 424 description (including transportation fuel). *Strict non-durable*: are non-durable categories that follow the definition proposed by Lusardi (1996): it excludes education related expenses, health-related expenditures and semi-durables.

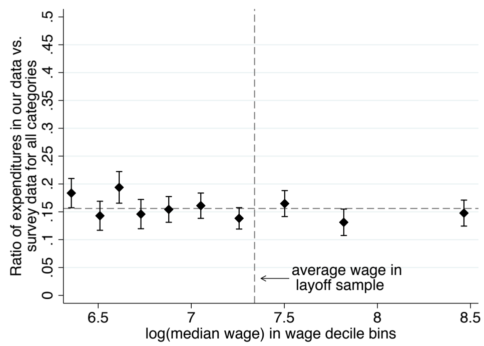
Table B2: Cross-walk between subcategories of non-durables used in the paper and sector of activity (CNAE)

Category		CNAE	CNAE description
Home Improvement		4741500	Comércio varejista de tintas e materiais para pintura
		4742300	Comércio varejista de material elétrico
		4744001	Comércio varejista de ferragens e ferramentas
		4744002	Comércio varejista de madeira e artefatos
		4744005	Comércio varejista de materiais de construção não especificados anteriormente
		4744099	Comércio varejista de materiais de construção em geral
Pharmaceutical		4771701	Comércio varejista de produtos farmacêuticos, sem manipulação de fórmulas
Food	*Food away*	5611201	Restaurantes e similares
		5611203	Lanchonetes, casas de chá, de sucos e similares
	Groceries	4711301	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - hipermercados
		4711302	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - supermercados
		4712100	Comércio varejista de mercadorias em geral, com predominância de produtos alimentícios - minimercados, mercearias e armazéns
		4721102	Padaria e confeitaria com predominância de revenda
		4722901	Comércio varejista de carnes - açougues
		4729699	Comércio varejista de produtos alimentícios em geral ou especializado em produtos alimentícios não especificados anteriormente

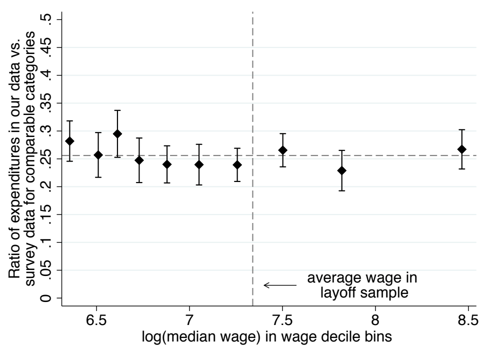
Notes: The table lists the cross-walk between subcategories of non-durable spending used in the paper and the sector of activity of the shops (CNAE) that issue the receipts. The list displayed in the table restricts attention to the top 7-digit CNAE codes in each category in terms of number of receipts that add up to 95% of all receipts in that category. *Home improvement*: CNAE codes with descriptions related to construction materials or tools. *Pharmaceutical*: CNAE codes with descriptions related to drugstores or health-care spending. *Food away* from home: CNAE codes with descriptions associated to food sold and typically prepared and consumed outside the home such as restaurants. *Groceries*: CNAE codes with descriptions associated to grocery shops or retail of food that is prepared at home.

Figure B2: Share of expenditure coverage by wage group

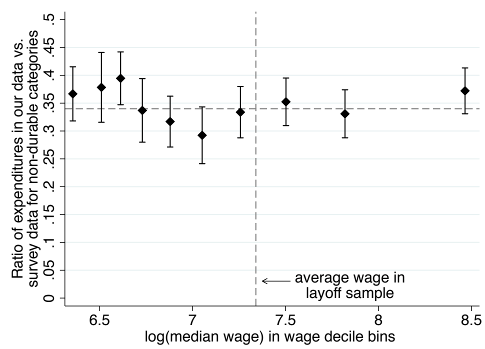
(a) Total expenditures



(b) Comparable categories



(c) Non-durables



Notes: The figure provides evidence supporting the quality of our de-identified expenditure data. Panels (a) - (c) display the ratio of average expenditures as measured in our data and in the latest round of the Survey of Household Expenditures (POF) by wage decile for workers formally employed at the time of the interview (survey data) and on December 31st (our data) in São Paulo. Average expenditure levels are estimated for each decile and dataset separately before taking their ratio (95% confidence intervals are calculated using the delta method). In Panel (a) we include all expenditures in both datasets (including spending categories in POF that are not covered in our data). Panel (b) shows the same graph as in Figure 3a: comparable categories. Panel (c) shows the ratio for goods classified as non-durables, which is defined in both datasets as described in Table B1. In all graphs, we reweight our data to match the distribution in the survey data of demographic characteristics observed in both datasets (quartiles of age, dummy variables for being white, having a high school degree, and being female). The vertical line indicates the average wage in our analysis sample as a reference. The horizontal line indicate the average ratio across wage deciles. In the three cases, the average is within the 95% confidence interval for most estimates across wage bins.

Online Appendix C - Survey conducted with workers in São Paulo

In this appendix we describe a survey that we conducted in the city of São Paulo, Brazil between July 23rd 2018 and August 3rd 2018. We focus on the key aspects of the survey that we discuss in the paper, and provide the relevant details of the data collection process.

Location. The interviews were conducted at the *Poupatempo* centers, which are popular one stop-shop citizen service centers used for a variety of services (e.g., driver's licence services, ID services, free internet through public computers *Acessa São Paulo*, etc.), of *Sé* and *Taquera*, and at the subway station *Bras*. These locations were chosen based on the fact that they have high foot traffic in general, and have an office where workers can claim UI benefits: a "Posto de Atendimento ao Trabalhador" (PAT).

Targeted population. The survey was targeted to two groups of workers: (i) *UI applicants*: workers who were laid off in the past 6 months from a formal job and applied for UI in the past 30 days (typically just before the interview as our interviews were conducted outside PATs); (ii) *Formal employees*: workers that, at the moment of the survey, were employed in the formal sector. We define "formal job" as a job in which the employer signed the worker's working card, which is mandatory and is the key paperwork to ensure that workers are protected by labor laws.

Analysis sample. For both samples, we restrict attention to workers with tenure lower than 72 months, which is one of the sample restrictions that we apply in our data in order to accurately calculate the statutory lump-sum benefits workers are eligible for (see Section I).

Results. Table C1 displays descriptive statistics related to demographic characteristics, which we refer to in the paper. The first column restricts attention to the sample of *UI applicants*, and the second column shows the results for *Formal employees*. Table C5 shows the questionnaire's questions from which we created the variables described in Table C1.

Table C2 displays descriptive statistics related to the layoff experience. Thus, it restricts attention to the sample of *UI applicants*. Table C6 shows the questionnaire's questions from which we created the variables described in Table C2.

Table C.3. describes the top 3 categories of uses for the lump-sum benefits that workers have access to after layoff (*UI applicants* only). The idea is to capture what is "top of mind" when respondents are asked about "*How did you use, or how do you intend to use the amount received after layoff?*". The figure in the table for each category corresponds to the share of workers that mention that category among their top 3 uses.

Table C4 shows how much support some hypothetical reforms on the disbursement of benefits would have among the survey respondents. The survey questions that were used to construct the variables in Table C4 are listed in Table C7. The question about UI benefits was only asked to *UI applicants*, whose application had already been approved. The question about FGTS contributions was asked to both samples. The questions about unconditional access to the FGTS balance every three years was asked only to *formal employees*. The qualitative answers provided by respondents to justify their response were summarized by "key message" by the survey company directly, and then further aggregated by the research team for the categories mentioned in the table.

Table C1 : Characteristics of survey respondents

	UI applicants	Formal employees
(mean at/before layoff)	(1)	(2)
Share female	0.51	0.49
Age (years)	34.21	37.58
Share with high school degree	0.75	0.88
Share white	0.45	0.51
Household size	2.84	2.85
Number of adults in household	1.99	2.20
Share with smartphone	0.91	0.98
Share with bank account	0.93	0.99
Tenure (months)	29.42	115.19
Share with wage up to 2 minimum wages	0.57	0.45
Share with wage between 2 and 3 minimum wages	0.23	0.10
Share with wage between 3 and 5 minimum wages	0.10	0.25
Share with wage above 5 minimum wages	0.11	0.20
Share with household income up to 2 minimum wages	0.29	0.19
Share with household income between 2 and 3 minimum wages	0.25	0.16
Share with household income between 3 and 5 minimum wages	0.22	0.18
Share with household income above 5 minimum wages	0.24	0.47
Share with any savings	0.43	0.53
Total savings (in monthly wages)	2.04	3.69
Share with any debts	0.59	0.60
Total debts (in minimum wages)	7.15	15.50
Share participating in Nota Fiscal Paulista (NFP)	0.51	0.60
Share using unique CPF for the whole household for NFP	0.62	0.61
Number of observations	136	139

Notes: The table displays descriptive statistics from a survey conducted in the city of São Paulo, Brazil, between July 23rd 2018 and August 3rd 2018. The survey was targeted to two groups of workers: (i) *UI applicants*: workers that were laid off in the past 6 months from a formal job and applied for UI in the past 30 days; (ii) *Formal employees*: workers who, at the moment of the survey, were employed in the formal sector. Both samples were restricted to include workers with tenure lower than 72 months. *Wages*, *household income*, *savings*, and *debts* refer to the period before or at layoff for UI applicants. These variables were created based on the questionnaire' questions and answers displayed in Table C5. For more details on the Nota Fiscal Paulista (NFP) program see Section I or Naritomi (2019). Due to missing values, the sample size of column (1) is 135 for Share white and Share participating in NFP; the sample size for column (2) is 136 for Share white.

Table C2 : Experience at layoff

	UI applicants
Share that learned about their layoff in advance	0.63
How many months in advance? (months before layoff)	2.96
Share that experienced a lower wage growth prior to layoff	0.13
Share that withdrew from FGTS account before layoff	0.07
Share that received 1-month advance notice	0.84
Share that obtained or is about to obtain access to FGTS account	0.98
Share that obtained or is about to obtain access to the layoff "fine"	0.87
Value of FGTS + fine + advance notice if received (in monthly wages)	4.89
Share that did not or does not intend to withdraw all FGTS and fine if received	0.04
Number of observations	136

Notes: This table describes the experience of workers at layoff in terms of the timing in which they learned about their layoff and their access to job displacement insurance benefits. It restricts attention to the sample of UI applicants. The survey questions used to construct the variables in this table are displayed in Table C6. FGTS is the forced savings accounts discussed in section I.

Table C3: Use of Job Displacement Insurance Benefits

	UI applicants
Share mentioning following category as (intended) use of lump-sum amount (FGTS and SP)	
(respondents could mention up to 3 categories)	
Non-durables (supermarket, clothing, food, etc.)	0.45
Durables (appliances, electronics, vehicles, furniture, etc.)	0.10
Special occasions (leisure, party, travel, shows, etc.)	0.06
Household bills (water, electricity, internet, schools, insurance, house cleaning, etc.)	0.46
Personal services (gym, beauty salon, etc.)	0.02
Home improvements	0.03
Debt repayment (excluding mortgages)	0.23
Mortgage payment	0.05
Investment in own business (goods for resale, materials, etc.)	0.04
Savings for long-term objectives (retirement, savings for university, etc.)	0.13
Savings for short-term objectives (emergencies, more expensive goods, travels, etc.)	0.27
Rent	0.01
Transfer to friends and family (gift, helping family or friend, etc.)	0.02
Other	0.07
Number of observations (only respondents who already received and withdrew FGTS and SP)	99

Notes: This table describes the answers to the question "*How did you use, or how do you intend to use the amount received after layoff? (Spontaneous answer: record the top 3 answers)*". The question refers to the lump-sum amount (FGTS + fine) described in section I, and records the top 3 categories of use for these benefits that respondents spontaneously listed when prompted by the question. The second column shows the share of respondents that listed the category in the first column among their top 3 uses for the lump-sum amount. The idea is to capture what is "top of mind", i.e. most salient, when thinking about the uses for these benefits. The question was only asked to UI applicants who had already received and withdrew their FGTS and SP amount.

Table C4: Support for hypothetical reform

	UI applicants	Formal employees
	(1)	(2)
Share preferring UI benefits paid in lump-sum fashion at layoff	0.40	
If no, reason for answer "To control expenditures"	0.39	
If no, reason for answer "To not spend it all at once"	0.36	
If no, reason for answer related to controlling expenditures	0.23	
If no, reason for answer unrelated to controlling expenditures ("It's not necessary at the moment")	0.03	
Number of observations (only respondents with UI application approved already)	121	
Share preferring monthly FGTS contributions as wage instead of forced savings deposits	0.47	0.43
If no, reason for answer "It is better to save"	0.21	0.5
If no, reason for answer "More money at layoff"	0.15	0.03
If no, reason for answer "I would/could spend it all/risk spending"	0.1	0.28
If no, reason for answer "It's safer in case of layoff / for insurance"	0.15	0.07
If no, reason for answer clearly related to controlling expenditures/saving constraints	0.19	0.15
If no, reason for answer possibly related to controlling expenditures/saving constraints	0.10	0.04
If no, reason for answer unrelated to controlling expenditures/saving constraints (e.g., "Greater value at the end", "The monthly value is small")	0.09	0.00
Number of observations	135	138
Share preferring unconditional access to FGTS account every 3 years		0.75
Number of observations		137

Notes: This table describes the answers to the questions on hypothetical reforms to the benefits workers currently have access to. The question about UI benefits was only asked to UI applicants, whose application had already been approved. The question about FGTS contributions was asked to both samples. The questions about unconditional access to the FGTS balance every three years was asked only to formal employees. The questions used in the survey to construct the variables in this table are displayed in Table C7. FGTS is the forced savings accounts discussed in section I. The qualitative answers provided by respondents to justify their response were summarized by "key message" by the survey company directly, and then further aggregated by the research team for the categories mentioned in the table.

Table C5: Survey questions for Table C1

Variable	Question	Answers
Share female	*Gender*	*(1) Male (2) Female*
Age (years)	*Age*	*(1) 16/24 (2) 25/34 (3) 35/44 (4) 45/59 (5) 60 OR +*
Share with high school degree	*What is the highest degree or level of schooling that you have completed? (Spontaneous answer)*	*(01) Illiterate (02) First primary incomplete (03) First primary complete (04) Second primary incomplete (05) Second primary complete (06) High school incomplete (07) High school complete (08) Undergrad incomplete (09) Undergrad (10) Master's (11) Phd*
Share white	*How would you describe yourself in terms of race? (Spontaneous answer)*	*(1) White (2) Indigenous (3) Black (4) Yellow (Asian) (5) Parda (6) Other*
Household size	*How many people depend on your household total income?*	*[insert text]*
Number of adults in household	*Number of adults, including you (at least 18 years old)*	*[insert text]*
Share with smartphone	*Do you own one of the following: smartphone*	*(1) yes (2) no*
Share with bank account	*Do you own one of the following: bank account*	*(1) yes (2) no*
Tenure (months)	*Before your layoff, for how long were you in this job? (At least 12 months)*	*_________ Year _________ Month*
Wage	*Among these income brackets (show the card with income brackets), where does the gross monthly salary that you had before layoff fit in? (CONSIDER additional salary, such as additional pay for night shift and hazard pay, and bonus. Do not consider benefits such as vale-refeição (food voucher), vale transporte (transportation voucher), and health insurance).*	*(1) up to 1/2 MW (up to R$468)* *(2) from 1/2 to 1 MW (R$468,1 to R$937)* *(3) from 1 to 2 MW (R$937,1 to R$1.874)* *(4) from 2 to 3 MW (R$1.874,1 to R$2.811)* *(5) from 3 to 5 MW (R$2.811,1 to R$4.685)* *(6) from 5 to 7 MW (R$4.685,1 to R$6.559)* *(7) from 7 to 10 MW (R$6.559,1 to R$9.370)* *(8) from 10 to 20 MW (R$9.370,1 to R$18.740)* *(9) more than 20 MW (more than R$18.740)*
Household income	*Among these income brackets (show the card with income brackets), where does your household total income that you had before layoff fit in? (Consider the income of everyone who contributes and all types of income sources: work, own business, rent, governmental transfers, etc.)*	*(1) up to 1/2 MW (up to R$468)* *(2) from 1/2 to 1 MW (R$468,1 to R$937)* *(3) from 1 to 2 MW (R$937,1 to R$1.874)* *(4) from 2 to 3 MW (R$1.874,1 to R$2.811)* *(5) from 3 to 5 MW (R$2.811,1 to R$4.685)* *(6) from 5 to 7 MW (R$4.685,1 to R$6.559)* *(7) from 7 to 10 MW (R$6.559,1 to R$9.370)* *(8) from 10 to 20 MW (R$9.370,1 to R$18.740)* *(9) more than 20 MW (more than R$18.740)*
Share with any savings	*Before layoff, were you able to monthly save part of your household income? For what purpose? (read the options and select which one that applies):*	*[1] Yes, for short-term purposes (emergencies, trips, expensive purchases, house improvement, etc.)* *[2] Yes, for long-term purposes (retirement, future expenditures to get children in college...)* *[3] No, I wasn't able to save*
Total savings (in monthly wages)	*At the moment of layoff, what was the total amount of savings that you had access to in terms of monthly wages before layoff?*	*__________ Months of wage*
Share with any debts	*Did you have debt?*	*(1) Yes (2) No*
Total debts (in monthly wages)	*What was the total value of debts that you had to pay in terms of monthly wage just before layoff?*	*The value was______________________________ months of wage.*
Share participating in Nota Fiscal Paulista (NFP)	*Are you a participant in the Nota Fiscal Paulista program?*	*(1) Yes (2) No*
Share using unique CPF for the whole household for NFP	*In your household, does everyone use the same CPF to request the Nota Fiscal Paulista? (read options)*	*(1) Yes, my CPF (2) Yes, the CPF of another person in the household (3) No*

Notes: The Variable column displays the variables reported in Table C1. The Question column contains the English translation of the questions that were used to create these variables. The Answers column shows the possible alternatives enumerators could choose from. The text in both columns were freely translated from the Portuguese original to English. MW is short for Minimum Wages, which was R$937 at the time of the interview.

Table C6: Survey questions for Table C2

Variable	**Question**	**Answers**
Learned in advance about layoff	*Informally, did you know about your layoff before it happened?*	*(1) Yes, I knew more or less about it.* *(2) No, it was a surprise*
How many months in advance? (months before layoff)	*If the answer is yes, approximately for how much time before did you know about it?*	*How many months before layoff did you know about it? ______ Months before layoff*
Experienced a lower wage growth prior to layoff	*In the months before layoff, did you receive smaller wage readjustments or did your wage start to decrease (through working hours reduction, less additional hours, none wage readjustment, etc.) comparing with the period before?*	*(1) Yes (2) No*
Withdrew from FGTS account before layoff	*Did you withdraw part of your FGTS relative to this job before layoff?*	*(1) Yes (2) No*
Did not receive 1-month advance notice	*Did you receive an advance notice?*	*(1) Yes (2) No*
Got or is about to get access to FGTS account		
Got or is about to get access to severance pay	*Did you have access to your FGTS balance and to your FGTS fine (40%) after layoff? If the answer is yes, how many months of wage the entire amount was equivalent to? (Read the options and select the closest answer)*	*(1) Yes, but only FGTS, and how many months of wage it was? _____ Months of wage* *(2) Yes, but only the FGTS fine, and how many months of wage it was? _____ Months of wage* *(3) Yes, both FGTS and its fine, and how many months of wage it was? _____ Months of wage* *(4) No*
Value of FGTS and severance pay if received (in monthly wages)		
Did not or does not intend to withdraw all FGTS and severance pay if received	*Did you withdraw all these resources (FGTS balance and its fine (40%))? (Read the options and select the nearest one)*	*(1) Yes, I withdrew all of it (2) No, I withdrew only a part of it (3) No, I didn't withdraw any of it*

Notes: The Variable column displays the variables reported in Table C2. The Question column contains the English translation of the questions that were used to create these variables. The Answers column shows the possible alternatives enumerators could choose from. The text in both columns were freely translated from the Portuguese original to English. FGTS is the forced savings accounts discussed in section I.

Table C7: Survey questions for Table C4

Variable	Question	Answers
Prefers UI benefits paid in lump-sum fashion at layoff	*Would you prefer to receive all the amount of unemployment insurance in one installment (the same way it occurs with FGTS and its fine payment)?*	*(1) Yes (2) No. Why?* ___________________
Prefers monthly FGTS contributions as wage instead of forced savings deposits	*Would you prefer if, as a formal employee, the FGTS deposits were made directly into your account along with your wage, instead of being deposited into that account that your normally do not have access to as an employee? (the net amount would be exactly the same)*	*(1) Yes (2) No. Why?* ___________________
Prefers unconditional access to FGTS account every 3 years	*Would you prefer if, while formally employed, the deposits in FGTS were made available every three years irrespective of layoff, health issues or use of these resources?*	*(1) Yes (2) No. Why?* ___________________

Notes: The Variable column displays the variables reported in Table C4. The Question column contains the English translation of the questions that were used to create these variables. The Answers column shows the possible alternatives enumerators could choose from. The text in both columns were freely translated from the Portuguese original to English. FGTS is the forced savings accounts discussed in section I.

Online Appendix D - Dataset on the prevalence of job displacement insurance programs across countries

This Appendix briefly describes the construction of the dataset documenting the prevalence of job displacement insurance (government-mandated) programs around the world since the start of the 20th century, which we use to construct Figure 1 in the paper.

Methodology

We worked with a team of Columbia undergraduates from many different parts of the world over a period of about six months, under the constant supervision of a PhD student in the Economics department, to create this dataset. In a first step, each undergraduate student was responsible for a set of countries (given their language proficiencies) and was instructed to find the necessary sources of information in order to document the existence and history of four sets of government-mandated programs (UI, SP, SSA, and UISA) since 1900 in each country. Effectively, given the many challenges involved, students often helped each other at this stage (they all met on a weekly basis). In a second step, another undergraduate student from the team verified the information for each country and coded it in a binary fashion, i.e., whether a significant version of each of the 4 programs existed in the country at some point for each decade since 1900. This step naturally involves some difficult decisions, so the students were instructed to justify all their decisions carefully. Using a binary classification also avoids the issue of comparing the generosity of programs along their many different policy parameters (it is much easier to go back in time to find information on the existence of a program than to find information on all its benefit schedules). In a third step, the PhD student reviewed all the data and the consistency of the coding across countries.

Output

The output of this work is twofold:

A. Data. A dataset documenting for 168 countries (according to 2018 borders) the existence of a significant version of each of the 4 programs in the country at some point for each decade since 1900. When some difficult coding decision was involved, a note explains the reason for our coding decision.

B. Documentation. A summary of the history of the 4 programs since 1900 for each of the 168 countries, including a list of the references used for each country.

The data and documentation will be made publicly available on our websites and we hope that it will be useful for other scholars across the social sciences. Any feedback to improve our coding decisions in specific instances will be much appreciated.

Note for Figure 1

The group of 25 countries labelled under "Western Europe, USA, CAN, AUS, NZ" in Figure 1 includes: Andorra, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Liechtenstein, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United States, and the United Kingdom.

The group of 114 countries labelled under "Africa, Asia, Rest of Americas" in Figure 1 includes: Afghanistan, Algeria, Angola, Argentina, Bahrain, Bangladesh, Benin, Bhutan, Bolivia, Botswana, Brazil, Brunei, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Republic of the Congo, Costa Rica, Cote d'Ivoire, Cuba, Cyprus, Democratic Republic of Congo, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Hong Kong, Haiti, Honduras, India, Indonesia, Iran, Iraq, Israel, Jamaica, Japan, Jordan, Kenya, Kuwait, Laos, Lebanon, Lesotho, Liberia, Libya, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Puerto Rico, Qatar, Rwanda, São Tome e Principe, Saudi Arabia, Senegal, Sierra Leone, Singapore, South Africa, South Korea, Sri Lanka, Sudan, Suriname, Swaziland, Syria, Taiwan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Tunisia, Turkey, UAE, Uganda, Uruguay, Venezuela, Vietnam, Yemen, Zambia, and Zimbabwe.

The data for 29 countries, mostly from Eastern Europe, were not used to generate the graphs in Figure 1: Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Fiji, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

REFERENCES

Ganong, Peter and Pascal Noel, "Consumer Spending during Unemployment: Positive and Normative Implications," *American Economic Review*, July 2019, *109* (7), 2383–2424.

Lanjouw, Peter, "Constructing a consumption aggregate for the purpose of welfare analysis: Issues and recommendations concerning the POF 2002/3 in Brazil," *Development Economics Research Group, World Bank. Mimeo*, 2005.

Lusardi, Annamaria, "Permanent income, current income, and consumption: Evidence from two panel data sets," *Journal of Business & Economic Statistics*, 1996, *14* (1), 81–90.

Naritomi, Joana, "Consumers as Tax Auditors," *American Economic Review*, September 2019, *109* (9), 3031–72.

Spinnewijn, Johannes, "Unemployed but optimistic: Optimal insurance design with biased beliefs," *Journal of the European Economic Association*, 2015, *13* (1), 130–167.