Online Appendix for:
The Welfare Effects of Involuntary Part-time Work

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Appendix A contains details on the motivating empirical evidence presented in Subsection 2.1 of the paper. Appendix B provides the information used to select the parameters of the model. Appendix C complements Section 5 of the paper, which analyzes the numerical experiments.

A Empirical Evidence

To gather the empirical evidence on involuntary part-time work discussed in Subsection 2.1, we use data from the monthly files of the Current Population Survey (CPS). There was a major overhaul of the CPS in 1994, which affects the measurement of part-time employment drastically. Therefore we restrict ourselves to CPS data from January 1994 onwards.

A.1 Characteristics of Involuntary Part-time Workers

In Table 1, we describe involuntary part-time workers in terms of their population characteristics. By comparing them to voluntary part-time workers (column 3 vs. column 2), we find a number of noticeable differences. For instance, while part-time work is strongly skewed toward women, involuntary part-time employment is much closer to parity (55.3% of involuntary part-timers are female workers). In addition, involuntary part-time workers are more likely to fall within the 25–54 age bracket. There are also significant differences between involuntary and voluntary part-time workers with respect to educational attainment, which is lower among involuntary part-time workers.

To get some perspective, in columns 4 and 5 of Table 1 we describe the population characteristics of unemployed workers. We distinguish between unattached workers (those who are new-entrants or re-entrants to the workforce) and attached workers (the remainder of the unemployed population). The composition of the pool of involuntary part-timers is strikingly similar to that of attached unemployed workers. In short, these individuals are more likely to be men in their prime age (which coincides with stronger labour force attachment), with lower-than-average employment opportunities (lower education levels), and less likely to be married.

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Table 1. Cross-sectional characteristics of part-time work and unemployment

	Labour force	Part-time work		Unemployment	
		Voluntary	Involuntary	Unattached	Attached
	(1)	(2)	(3)	(4)	(5)
(a) Gender					
Men	53.5	29.8	44.7	45.9	62.4
Women	46.5	70.2	55.3	54.1	37.0
(b) Age					
16 to 24 years	15.6	36.9	29.7	54.4	21.0
25 to 54 years	71.4	49.6	60.9	41.0	68.0
55 to 64 years	12.9	13.5	9.4	4.9	10.3
(c) Education					
Less than high-school	11.9	18.3	21.5	35.6	18.7
High-school graduates	30.1	24.3	37.7	29.2	38.7
Some college	24.4	31.7	22.7	22.0	23.0
College or higher education	29.0	21.8	14.5	11.2	14.8
(d) Marital status					
Married	56.1	46.3	36.3	23.1	40.7
Widowed; divorced; separated	14.1	9.3	16.6	10.8	17.4
Single	29.7	44.5	47.1	66.5	40.3

Notes: Authors' calculations based on CPS data for the period 1994m01–2015m12. All entries are reported in percent.

A.2 Dynamics of Involuntary Part-time Work

To inform our characterization of the dynamics of involuntary part-time work, we use linked CPS data to estimate transition probabilities. We classify workers in five labour market states: full-time work (F), part-time work, voluntary (V) or not (I), unemployment (U) and non-participation (N). We follow the estimation protocol presented in Borowczyk-Martins and Lalé [2016b]. In particular, we implement a correction for transitions between voluntary (V) and involuntary (I) part-time work, and transitions between non-participation (N) and unemployment (U), both of which appear spuriously common in the raw data. As per the estimation protocol, the time series that we obtain control for seasonality, margin-error problems and time-aggregation bias.

In order to maximize consistency between data and the assumptions of our model, we estimate transition probabilities for prime-age workers who are non-married and are without children.

Transition probabilities

Table 2 reports sample averages of inflow and outflow transition probabilities for involuntary part-time work (left panel) and unemployment (right panel).[1] For completion, in this table we report transitions between I, V, N in the left panel, and U, V, N in the right panel, although these do not have a counterpart in the model. The point is to explain how we calculate the total monthly inflow and outflow probabilities displayed in the last row of Table 2.

[1]The inflow transition probability from i to j at time t, denoted $q(i \to j)$, is the ratio of the gross flow of workers moving from i to j at time t divided by the number of workers in j at time t. The outflow transition probability from i to j at time t, denoted $p(i \to j)$, is the ratio of the gross flow of workers moving from i to j at time t divided by the number of workers in i at time $t-1$.

Table 2. Sample averages of monthly transition probabilities

Involuntary part-time work				Unemployment			
Inflows		Outflows		Inflows		Outflows	
$q(F \to I)$	29.6	$p(I \to F)$	28.9	$q(F \to U)$	18.3	$p(U \to F)$	15.8
$q(V \to I)$	16.7	$p(I \to V)$	15.1	$q(V \to U)$	3.63	$p(U \to V)$	3.74
$q(U \to I)$	12.4	$p(I \to U)$	8.85	$q(I \to U)$	3.97	$p(U \to I)$	5.64
$q(N \to I)$	4.65	$p(I \to N)$	3.58	$q(N \to U)$	9.11	$p(U \to N)$	7.88
$\sum_{i \neq I} q(i \to I)$	63.3	$\sum_{j \neq I} p(I \to j)$	56.4	$\sum_{i \neq U} q(i \to U)$	35.0	$\sum_{j \neq U} p(U \to j)$	33.1

Notes: Authors' calculations based on CPS data for the period 1994m01–2015m12. The sample includes all individuals aged 25 to 54 who are non-married and are without children. All entries in the table are reported in percent.

The high levels of transition probabilities at the bottom of Table 2 underscore one of our claims, that involuntary part-time work and unemployment are both transitory labour market states. For instance, when looking at involuntary part-time workers, we observe that roughly two thirds (63.3%) of these workers were in a different labour market state (F, V, U or N) in the previous month. It is noticeable that, during this period, the inflow and outflow transition probabilities (respectively at 35.0% and 33.1%) of unemployment are low compared to historical U.S. averages. As a result, the dynamics of involuntary part-time work look by comparison extremely fast.

The second fact worthy of attention in Table 2 is that involuntary part-time work and unemployment are both highly connected to full-time employment. For example, 29.6% of all involuntary part-time workers were employed full-time in the previous month, and 28.9% will enter full-time employment next month. The corresponding figures for unemployment are 18.3% and 15.8%. In relative terms, transitions from (into) full-time employment account for *half* of the inflows (outflows) of both involuntary part-time work and unemployment.

Within-employer transitions

An important fact concerning the source of transitions between involuntary part-time and full-time employment is that they take place overwhelmingly at the same employer. Table 3 illustrates this point with statistics on the share of transitions occurring at the same employer.

Table 3. Transitions between full-time and involuntary part-time work

Share of transitions at the same employer			
$F \to I$	93.5	$I \to F$	90.4

Notes: Authors' calculations based on CPS data for the period 1994m01–2015m12. The sample includes all individuals aged 25 to 54 who are non-married and are without children. All entries in the table are reported in percent.

We observe that, on average, 90.4% of transitions from involuntary part-time work to full-time employment ($I \to F$) occur without a change in employer. This pattern underscores our findings regarding the premium enjoyed by part-time workers in returning to full-time work. We elaborate further on this result in Section 6 of the paper.

A.3 U.S. Institutions and Policies

We use data from various sources in order to offer empirical evidence about the U.S. public programs that may provide some degree of insurance to involuntary part-time workers. For partial UI and STC schemes, we use data provided by the Employment and Training Administration of the U.S. Department of Labor (DOLETA). For the EITC, we use data from the Congressional Research Service. We combine these data with state-specific time series of involuntary part-time employment for the overlapping period, which we construct using the methodology presented in Borowczyk-Martins and Lalé [2016b]. We now provide details on our empirical work.

Partial Unemployment Insurance. To assess the coverage of partial UI, we collect state-level data published by the DOLETA (available at `http://oui.doleta.gov/unemploy/`) on the amount of benefits effectively paid in partial and full unemployment insurance. The amount paid in partial unemployment insurance is the total value of benefits paid to individuals who earn above the state's disregard level. We link these data to time series of stocks of unemployed and involuntary part-time workers to obtain estimates of the monthly UI payments per unemployed worker and involuntary part-time worker. The final time series, displayed in Figure 1 of the paper, are expressed in constant 2009 U.S. dollars based on the Personal Consumption Expenditures Price Index.

Let us comment briefly on our somewhat surprising finding, that the UI amount paid per involuntary part-time worker is very low. Our conjecture is that workers who are experiencing short-time work at their employer (the bulk of involuntary part-time workers) have little incentives to claim partial UI. In this regard, Le Barbanchon [2016]'s case-study of the utilization of partial UI in the states of Idaho, Louisiana, Missouri and New Mexico during the late 1970s and early 1980s offers interesting insights. The author finds that eligibility of individuals who are experiencing short-time work at their employer is conditional on the presentation of an employer-certified reduction in hours worked. It is conceivable that, on top of this requirement, short-time workers face additional hurdles (e.g., at the UI agency, etc.) which prevent them from effectively claiming partial UI benefits.

Short-Time Compensation schemes. The data on the number of STC claims come from the DOLETA (`http://www.dol.gov/`). The data are available on a weekly basis, beginning on January 4, 1986. We merge the number of STC claims to the number of involuntary part-time workers in the 17 states with STC programs during the past thirty years (Arizona, Arkansas, California, Connecticut, Florida, Iowa, Kansas, Maryland, Massachusetts, Minnesota, Missouri, New York, Oregon, Rhode Island, Texas, Vermont, Washington). The resulting time series is shown in Figure 2 of the paper. Its low level dovetails with the small take-up rates reported by Abraham and Houseman [2014]. In their account of this policy, the authors also report small take-up rates even in industries where work-sharing programs are supposedly more prevalent (typically, the manufacturing sector).

In Table 1 of the same section, we report the number of UI claims divided by the number of unemployed workers in states with STC schemes. We downloaded the data on UI claims from `http:`

//www.workforcesecurity.doleta.gov/unemploy/finance.asp. Data on unemployment at the state level come from the Local Area Unemployment Statistics of the Bureau of Labor Statistics available at http://www.bls.gov/lau/.

The Earned Income Tax Credit. To assess the EITC's coverage we combine three data sources. The first source of data is from the Congressional Research Service (www.crs.gov), which provides information on the maximum phase-out income level of the EITC in each year for childless adults, families with one child, families with two children and families with three or more children. For example, in 2015, the maximum phase-out income level for families with two or more children is 44,454 U.S. dollars. The second data source are the annual demographic supplement files of the Current Population Survey (March CPS). We use information on total household income and money received from energy subsidies and food stamps. Then, in each group circumscribed by family structure and marital status, we estimate the fraction of households with income below the maximum phase-out income level of the corresponding year. This fraction provides us with an estimate of potential eligibility for the EITC based on the family structure and marital status of individuals. Although quite simple, this approach enables us to accurately predict the number of EITC recipients in each year since 1980: the overall R-square of the regression of the actual vs. the predicted time series is 93%. Finally, these estimates are matched to data on involuntary part-time workers from the monthly CPS using the same partition by family structure and marital status. The final estimates of potential EITC eligibility among involuntary part-time workers are plotted in Figure 3 of the paper.

B Parameter Choices

In this subsection, we present the empirical basis to ground the choice of parameter values in Section 4 of the paper. We begin with the evidence on hours and earnings, which are used to set several parameter values externally. Then we describe the data moments that discipline the model's calibration.

B.1 Hours Worked and Earnings

To gather evidence on hours worked and earnings, we pool data from the Outgoing Rotation Groups of the CPS for the period 2001m12–2007m11. We focus on this window because it spans a long period of time between the two recessions covered by our dataset.

Hours worked. Panel a. of Table 4 reports average and median hours worked in full-time, in overall part-time and in involuntary part-time employment. The gap in hours worked is close to 50 percent when we compare full-time with overall part-time employment, and is reduced when we only consider involuntary part-time work. The parameter values for h_P and h_F are chosen so as to match the values of median hours worked in full-time and involuntary part-time work shown in Table 4. In a previous version of the model, we selected values for h_P and h_F under the assumption that the gap in hours is exactly 50 percent; the results were similar to those obtained under the current parametrization.

Earnings. Our choice of parameter values for w_P and w_F is meant to include a part-time wage penalty, in line with a well-established literature on this topic (see footnote 2 below). Estimating the

Table 4. Hours and earnings in overall part-time and involuntary part-time work

a. Hours	Male workers			Female workers		
	Full-time	Part-time		Full-time	Part-time	
		Overall	Involuntary		Overall	Involuntary
Mean	43.7	21.6	24.0	41.4	21.4	23.6
Median	40.0	20.0	25.0	40.0	20.0	25.0

b. Earnings gap	Male workers			Female workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall part-time	-0.608	-0.288	-0.201	-0.323	-0.179	-0.112
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Involuntary part-time	-0.519	-0.274	-0.185	-0.397	-0.230	-0.134
	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Worker-level controls	N	Y	Y	N	Y	Y
Job-level controls	N	N	Y	N	N	Y

Notes: Authors' calculations based on CPS data, pooled outgoing rotation groups for the period 2001m12–2007m11. Panel a: Average and median hours worked in full-time, in overall part-time and in involuntary part-time employment. Panel b: Each entry is from a separate OLS regression of the log hourly earnings against a dummy for overall part-time work (first row) or involuntary part-time work (second row), and further controls at the worker-level (N/Y) and job-level (N/Y). Standard errors in parentheses.

wage penalty associated with involuntary part-time work is beyond the scope of our analysis. We nevertheless report results based on our own calculations, and that are very well-aligned with the findings from the literature.

Our variable of interest is (the log of) hourly earnings (including usual amounts of overtime, tips, commissions, and bonuses) trimmed at the bottom and top 1 percent of the distribution. We run several OLS regressions to estimate the wage penalty of overall part-time work as well as the penalty of involuntary part-time work. As can be observed in panel b. of Table 4, there is a significant and large earnings penalty in the raw data (columns 1 and 4): -60.8% (-32.3%) in overall part-time, -51.9% (-39.7%) in involuntary part-time for men (women). In line with the existing literature, we also find that individual controls account for a large share of the observed differential, and that including job characteristics further reduces the difference in earnings. After accounting for (observed) individual and job characteristics (columns 3 and 6), the part-time penalty is between -20.1% and -18.5% for men, and between -13.4% and -11.2% for women, very similar to estimates reported in the literature.[2] In the calibrated model, we take the part-time wage penalty to be -15%, a figure well within the range of the estimates presented in Table 4.

B.2 Asset Holdings

We use data from the Panel Study of Income Dynamics (PSID) to compare asset holdings and earnings. These comparisons help us choose a calibration target for the discount factor, β, and determine

[2] Similar results are found in specifications that are arguably more immune to endogeneity biases; see Hirsch [2005] who uses the panel structure of the CPS, and Aaronson and French [2004] who use administrative data.

the relevant range of asset holdings used to conduct our numerical experiments.

Data. The data come from the supplemental wealth files to the PSID for the years 1984, 1989, 1994 and for every two years from 1999 to 2007. These files contain information on eight broad wealth categories at the family level. Those include: (i) the value of checking and savings accounts, money market funds, certificates of deposit, savings bonds, Treasury bills and other individual retirement accounts (IRAs; IRAs are asked separately beginning in 1999), (ii) the value of shares of stock in publicly-held corporations, mutual funds or investment trusts, including stocks in IRAs, (iii) the value of other investments in trusts or estates, bond funds, life insurance policies and special collections, (iv) the value of debts other than mortgages, such as credit cards, student loans, medical or legal bills, personal loans, (v) the net value of real estate other than the main home, (vi) the net value of vehicles or other assets "on wheels", (vii) the value of home equity, calculated as home value minus remaining mortgage and (viii) the net value of farm or business assets. We follow the study of precautionary savings by Carroll and Samwick [1998] and sum components (i), (ii) and (iii) to construct a variable measuring *liquid* asset holdings.[3]

The wealth files can be matched to the core file of the PSID, which provides socio-demographic and income data at the family level. We restrict the sample to observations from the non-poverty subsample of the PSID, with households heads aged 25 to 54 and with at least 12 years of schooling. The objective of these restrictions is to obtain a sample that is representative of a large population while being sufficiently homogeneous to resemble our framework, which features no *ex ante* heterogeneity.

Analysis. Table 5 reports the mean value of three variables: liquid assets, annual earnings, and the ratio of liquid assets to annual earnings. Notice that the third row shows the mean of this ratio, which is different from taking the ratio of the mean of the first two variables.

Table 5. Asset holdings compared with annual earnings

	(1)	(2)	(3)
Average wealth (liquid assets), in 2000 U.S. dollars	15,920	15,306	13,058
Average annual earnings, in 2000 U.S. dollars	53,303	53,535	53,764
Ratio of wealth to annual earnings	0.29	0.27	0.22

Notes: Authors' calculations based on PSID data on households (non-poverty subsample) with head aged 25 to 55 years old and with at least 12 years of schooling. In column 2 (resp 3), the sample is trimmed at the 1st and 99th (resp. 5th and 95th) percentiles of the variable measuring the ratio of wealth to annual earnings.

The picture conveyed by Table 5 is readily described. When looking at liquid assets, we find that these amount to around a quarter of households' annual earnings. This average value is not too sensitive to the ratios observed at the two ends of the spectrum. As noted in the main text (see for instance Subsection 4.3), the figure is not unexpected in light of what the literature on precautionary savings documents. Table 5 motivates our focus on the trajectory of a worker who holds one quarter of annual earnings in savings to smooth out the shock of being separated from a full-time position.

[3] We focus on these categories since less liquid assets do not resemble the asset that the agent accumulates in our model. It seems likely that assets that cannot be liquidated without incurring a high transaction costs are less relevant to smooth out a temporary shocks to labour earnings.

In the calibration, the target used for β is a median asset level worth one half of the annual income of the worker. This value is higher than the wealth-to-income ratio computed in our data when we use liquid asset holdings. In fact, in the data the ratios are dragged down by a fraction of households with *negative* levels of wealth. Our model cannot speak to this feature because we preclude borrowing in order to economize on the number of parameters. Meanwhile, our calibration target implies a very high subjective discount rate: 15.2% on an annual basis. This is in line with the high subjective discount rates used in standard incomplete-market models in order to 'push' a fraction of agents towards the borrowing limit.

B.3 Transition Probabilities

For completeness, we explain how we calculate the data moments on labour market transitions that are used in the calibration. Based on Table 2, we compute the job-finding rate as the sum of transition probabilities $p(U \to F)$, $p(U \to V)$ and $p(U \to I)$. The latter component is the other data moment that we target in the calibration. We interpret it as a measurement of transitions from uninsured unemployment into involuntary part-time work.

C Numerical Experiments

This appendix complements Section 5 of the paper in two ways. Firstly, we give additional details on the numerical experiments conducted in Subsection 5.2, where we extend the model to study cyclical fluctuations in involuntary part-time work. The second part of this appendix reports the results from several robustness checks mentioned in the text.

C.1 Welfare costs of cyclical fluctuations in involuntary part-time risk

To recast the analysis of the business cycle within the context of the model, let us recall that we set $\pi_{F,P} = \bar{\pi}_{F,P}(1+\varepsilon_{F,P})$ and $\pi_{P,F} = \bar{\pi}_{P,F}(1-\varepsilon_{P,F})$ during bad times, and $\pi_{F,P} = \bar{\pi}_{F,P}(1-\varepsilon_{F,P})$ and $\pi_{P,F} = \bar{\pi}_{P,F}(1+\varepsilon_{P,F})$ during good times. The economy fluctuates between bad times and good times according to a symmetric Markov process.

Business-cycle patterns

Table 6 displays the empirical evidence that motivates our stylized characterization of short-run fluctuations. As is standard in business-cycle analysis, we study the cyclical component of quarterly time series taken in logs as deviations from a Hodrick-Prescott trend with parameter 10^5. In the table, we focus on $p(I \to F)$, $p(F \to I)$ and $p(U \to E)$.

The first row of Table 6 shows that $p(I \to F)$ and. $p(F \to I)$ deviate from their long-run value by on average 8.2% and 19.7%, respectively. Thus, by using $\varepsilon_{P,F} = 0.10$ and $\varepsilon_{F,P} = 0.20$ in the experiments, we replicate closely the business-cycle behaviour of these transition probabilities. Notice that we also explore the effects of raising $\varepsilon_{P,F}$ and $\varepsilon_{F,P}$ further to respectively 0.15 and 0.40. So doing, we aim at capturing the increased volatility of transition probabilities at the end of the sample period. The second part of Table 6 reports a set of correlation coefficients. They are all statistically significant at the 0.01 level. We observe, first of all, that the correlation between (the cyclical components of) $p(I \rightarrow F)$ and the job-finding rate ($p(U \rightarrow E)$) is positive and large, at 0.479. We do not introduce business-cycle variations in the job-finding rate (through, e.g., fluctuations in λ), but in our definition of tranquil economic times, we set $\varepsilon_{P,F}$ to 0.05 in order to account for this correlation. Second, we find that the correlation between (the cyclical components of) $p(I \rightarrow F)$ and $p(F \rightarrow I)$ is -0.358. This motivates our assumption of perfectly negatively correlated stocks, although the actual correlation is much below 1 in absolute value. By forcing a perfect correlation, we give the best chance for a large effect of business-cycle fluctuations.

Table 6. Business cycle moments of transition probabilities

		$p(I \rightarrow F)$	$p(F \rightarrow I)$	$p(U \rightarrow E)$
Std. Dev.		0.082	0.197	0.157
Correlation	$p(I \rightarrow F)$	1.0	-0.358	0.479
	$p(F \rightarrow I)$	–	1.0	-0.863
	$p(U \rightarrow E)$	–	–	1.0

Notes: Authors' calculations based on CPS data for the period 1994m01–2015m12. The time series are quarterly averages of the monthly series taken in logs as deviations from an HP trend with smoothing parameter 10^5.

In Subsection 5.2, we contrast the effects of fluctuations in transition probabilities around two steady-state values: $\bar{\pi}_{F,P} = 0.011$ and $\bar{\pi}_{F,P} = 0.022$. The motivation is straightforward. Over the entire sample period, the monthly transition probability $p(F \rightarrow I)$ is 1.12% on average. At the end of the Great Recession (more precisely: during the first two quarters of 2009), $p(F \rightarrow I)$ peaked at 2.16%. This transition probability has remained stubbornly high since then (see Borowczyk-Martins and Lalé [2016b]). Thus, we think the experiment is informative in that it explores an extreme scenario where $\bar{\pi}_{F,P}$ remains permanently elevated.

Welfare figures

In the experiment conducted in Subsection 5.2, we compare the lifetime values in full-time employment, when the cyclical risk of involuntary part-time work measured by $\varepsilon_{F,P}$ switches from 0 to a positive value. Let $W_F(a,z)$ (resp. $\widetilde{W}_F(a,z)$) denote the value of full-time work with asset a when the aggregate state of the economy is z and $\varepsilon_{F,P} = 0$ (resp. $\varepsilon_{F,P} > 0$). Given our choice of preferences, the change in lifetime consumption triggered by $\varepsilon_{F,P} > 0$, which we denoted as $\vartheta(a,z)$, satisfies:

$$1 + \vartheta(a,z) = \left[\frac{\widetilde{W}_F(a,z) + \frac{1}{1-\beta}\frac{1}{1-\sigma}}{W_F(a,z) + \frac{1}{1-\beta}\frac{1}{1-\sigma}} \right]^{\frac{1}{1-\sigma}}. \quad (1)$$

For all a, we aggregate $\vartheta(a,z_b)$ and $\vartheta(a,z_g)$ as follows. Since the Markov process for z is symmetric, the worker spend half of her time in $z = z_b$ and the other half in $z = z_g$. Therefore, we let

$$\vartheta(a) \equiv \frac{1}{2}\vartheta(a,z_b) + \frac{1}{2}\vartheta(a,z_g) \quad (2)$$

measure the welfare effect at the asset level a. Finally, in Table 5 of the paper, we report the *range* of values $\vartheta(a)$ computed over the support for asset holdings. This avoids aggregating the values $\vartheta(a)$ using some cross-sectional distribution of asset holdings. Moreover, it gives a good approximation of the average welfare effect since the range of computed values turns out to be quite narrow.

C.2 Sensitivity Analysis

Preference parameters. In table 7 we show the analogue of the results reported in Table 4 of the paper using different values for the relative utility of leisure, η. We report results based on a lower and higher relative value of leisure, namely $\eta = 0.25$ and $\eta = 0.75$. The calibration procedure for $\eta = 0.25$ yields: $\beta = 0.9905$, $\lambda = 0.3508$, $\phi_P = 0.1906$. For $\eta = 0.75$, the calibration procedure yields: $\beta = 0.9880$, $\lambda = 0.4328$, $\phi_P = 0.2218$.

With a lower value ($\eta = 0.25$) the gap in workers' welfare between involuntary part-time work and unemployment decreases, both for insured and uninsured unemployment (respectively from -7.633 to -4.567, and from -23.29 to -21.66). Inspection of the columns in each panel shows that all three components contribute to make unemployment relatively less costly than in the baseline scenario. With $\eta = 0.75$, the effect is the opposite (the value of the utility compensation increases). Our main finding, viz. the greater quantitative importance of 'access to full-time employment' in accounting for the welfare difference between involuntary part-time and insured unemployment, is still true in either of the two alternative parametrizations.

Table 7. Sensitivity analysis: The role of the utility of leisure

	1. Comparison with: Insured unemployment							
	a. $\eta = 0.25$				**b.** $\eta = 0.75$			
	$\triangle$ labour earnings (1a)	$\triangle$ access to full-time (2a)	$\triangle$ hours constraint (3a)	$\triangle$ total (4a)	$\triangle$ labour earnings (1b)	$\triangle$ access to full-time (2b)	$\triangle$ hours constraint (3b)	$\triangle$ total (4b)
1st quarter	-1.759	-3.038	0.230	-4.567	-2.527	-6.777	0.442	-8.862
2nd quarter	-1.238	-0.383	0.064	-1.557	-1.354	-0.530	0.146	-1.738
3rd quarter	-0.920	-0.314	0.065	-1.169	-1.084	-0.411	0.107	-1.387
	2. Comparison with: Uninsured unemployment							
	a. $\eta = 0.25$				**b.** $\eta = 0.75$			
	$\triangle$ labour earnings (1a)	$\triangle$ access to full-time (2a)	$\triangle$ hours constraint (3a)	$\triangle$ total (4a)	$\triangle$ labour earnings (1b)	$\triangle$ access to full-time (2b)	$\triangle$ hours constraint (3b)	$\triangle$ total (4b)
1st quarter	-15.57	-6.373	0.279	-21.66	-17.90	-8.527	0.211	-26.21
2nd quarter	-1.400	-0.963	0.230	-2.132	-1.985	-1.654	0.531	-3.108
3rd quarter	-1.040	-0.614	0.210	-1.443	-1.178	-0.674	0.306	-1.545

Notes: An entry in the table is the change (reported in percent) in quarterly consumption. The upper (resp. lower) panel of the table compares part-time employment with insured (resp. uninsured) unemployment, when wealth at the time of displacement amounts to one quarter of annual earnings. Columns 1a to 4a (resp. 1b to 4b) report results based on a low (resp. high) utility of leisure.

Table 8 is the analogue of Table 5 in the paper, except that the coefficient of relative risk aversion is changed to either $\sigma = 1.0$ or $\sigma = 3.0$. In Table 8, we use the baseline specification for η, i.e. $\eta = 0.50$. For $\sigma = 1.0$, the calibrated parameters are $\beta = 0.9963$, $\lambda = 0.5187$, and $\phi_P = 0.1749$, while under $\sigma = 3.0$ the calibrated parameters are $\beta = 0.9715$, $\lambda = 0.4484$, and $\phi_P = 0.2218$. The results are remarkably consistent with the baseline specification: the order of magnitude of the welfare figures is unchanged, and hence these remain far below the costs of business cycle fluctuations in unemployment typically found in the literature. It is worth noting that varying the parameter σ leads to large changes in the subjective discount factor, β, as per the calibration procedure (recall that σ is also the inverse of the elasticity of intertemporal substitution). These changes could in turn explain the invariance of the results.

Table 8. Sensitivity analysis: The role of relative risk aversion

		1. $\sigma = 1.0$		
Deviations around:	**a.** $\bar{\pi}_{F,P} = 0.011$		**b.** $\bar{\pi}_{F,P} = 0.022$	
	$\varepsilon_{F,P} = 0.20$	$\varepsilon_{F,P} = 0.40$	$\varepsilon_{F,P} = 0.20$	$\varepsilon_{F,P} = 0.40$
$\bar{\pi}_{P,F} = 0.261$	(1)	(2)	(3)	(4)
$\varepsilon_{P,F} = 0.05$	[-0.009, -0.008]	[-0.015, -0.014]	[-0.013, -0.012]	[-0.014, -0.012]
$\varepsilon_{P,F} = 0.10$	[-0.026, -0.025]	[-0.042, -0.040]	[-0.043, -0.042]	[-0.063, -0.059]
$\varepsilon_{P,F} = 0.15$	[-0.047, -0.046]	[-0.074, -0.072]	[-0.081, -0.079]	[-0.119, -0.115]
		2. $\sigma = 3.0$		
Deviations around:	**a.** $\bar{\pi}_{F,P} = 0.011$		**b.** $\bar{\pi}_{F,P} = 0.022$	
	$\varepsilon_{F,P} = 0.20$	$\varepsilon_{F,P} = 0.40$	$\varepsilon_{F,P} = 0.20$	$\varepsilon_{F,P} = 0.40$
$\bar{\pi}_{P,F} = 0.261$	(1)	(2)	(3)	(4)
$\varepsilon_{P,F} = 0.05$	[-0.012, -0.011]	[-0.018, -0.014]	[-0.015, -0.012]	[-0.014, -0.000]
$\varepsilon_{P,F} = 0.10$	[-0.036, -0.033]	[-0.055, -0.052]	[-0.054, -0.051]	[-0.077, -0.062]
$\varepsilon_{P,F} = 0.15$	[-0.066, -0.062]	[-0.100, -0.094]	[-0.103, -0.098]	[-0.150, -0.134]

Notes: An entry in the table is the range of welfare effects computed at different levels of asset holdings. The welfare effects measure the percentage change in lifetime consumption of an increase in the cyclical risk of involuntary part-time employment. The top and bottom left (resp. right) panel of the table shows the effects of deviations around the monthly transition probability $\bar{\pi}_{F,P} = 0.011$ (resp. $\bar{\pi}_{F,P} = 0.022$). The top (resp bottom) panel is based on the model calibrated with $\sigma = 1.0$ (resp. $\sigma = 3.0$).

Other robustness checks. Table 9 reports the results from changing the asset levels of individuals at the time of job displacement. The features worth pointing out are as follows. First, in the comparison with insured unemployment, the relative value of total utility compensation changes little with the level of initial wealth. Second, the contribution of the various components is also robust to changing initial wealth. Third, in the comparison with uninsured unemployment, the level of initial wealth plays a more important role in changing both the levels and contribution of the different components. In particular, the effects of 'labour earnings' becomes more potent when assets are lower. In all instances, 'access to full-time employment' remains a major contributor to the short-run welfare difference between involuntary part-time work and unemployment.

A previous version of the paper contained results based on slightly different estimates for the transition matrix Π and other calibration targets for λ and ϕ_P. The results were qualitatively similar

Table 9. Sensitivity analysis: The role of asset holdings at the time of displacement

1. Comparison with: Insured unemployment

	a. a =1 month of earnings				**b.** a = 6 months of earnings			
	△ labour earnings (1a)	△ access to full-time (2a)	△ hours constraint (3a)	△ total (4a)	△ labour earnings (1b)	△ access to full-time (2b)	△ hours constraint (3b)	△ total (4b)
1st quarter	-1.886	-6.472	0.639	-7.719	-1.476	-4.399	0.790	-5.088
2nd quarter	-0.948	-0.595	0.197	-1.346	-0.506	-0.282	0.205	-0.584
3rd quarter	-0.627	-0.313	0.105	-0.835	-0.264	-0.066	0.046	-0.284

2. Comparison with: Uninsured unemployment

	a. a =1 month of earnings				**b.** a = 6 months of earnings			
	△ labour earnings (1a)	△ access to full-time (2a)	△ hours constraint (3a)	△ total (4a)	△ labour earnings (1b)	△ access to full-time (2b)	△ hours constraint (3b)	△ total (4b)
1st quarter	-22.57	-6.562	0.013	-29.12	-12.09	-6.875	0.203	-18.76
2nd quarter	-2.579	-2.019	0.492	-4.106	-1.143	-0.811	0.214	-1.739
3rd quarter	-1.794	-1.268	0.459	-2.603	-0.788	-0.452	0.146	-1.094

Notes: An entry in the table is the change (reported in percent) in quarterly consumption. The upper (resp. lower) panel of the table compares part-time employment with insured (resp. uninsured) unemployment, when wealth at the time of displacement amounts to one quarter of annual earnings. Columns 1a to 4a (resp. 1b to 4b) report results based on initial assets amounting to 1 month (resp. 6 months) of annual earnings.

to those reported in the paper. We refer the reader to Tables 8, 9, and C2 to C4 in Borowczyk-Martins and Lalé [2016a] for robustness checks with respect to Π, λ and ϕ_P.

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