Entrepreneurship and Labor Market Mobility: the Role of Unemployment Insurance

Online Appendix

Not to be considered for publication

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1 Empirical Appendix

1.1 Full details on the CPS sample

1.1.1 Sample construction

Throughout the paper, we use the IPUMS-CPS to compute both the masses in each occupation and the corresponding flows between them. We retain a sample from 1994 to 2015 and consider only the 20-65 years old population. We choose 1994 since key variables identifying self-employed business owners (HHBUS) are not available before. We build a quarterly panel of around 10 million matched individuals for the empirical section of the paper. In our empirical analysis, we use the longitudinal CPS weights: PANLWT.[1]

In order to control for false matches, we construct a specific individual identifier that controls for age, sex, ethnicity, and US state. Unfortunately, we are unable to track movers to a different US state. Unfortunately, if an individual is moving to another US state, we are not able to follow this individual. Probabilities are multiplied by the first-month respondent weight to generate a numeric value for the fraction of individuals in a specific occupation leaving to another occupation. Finally, we use only quarterly transitions for which we observe that individuals switched since at least two consecutive months to another occupation. For instance, U – – E – U transitions (from unemployment to entrepreneurship and back over the quarter) are recoded as U – – – U. We do a similar adjustment if we observe U – – U – E. As such, only U – – E – E observations are coded as U – – – E. This restriction aims to reduce the mismeasurement due to possible misreporting as highlighted in Farber et al. (2015). Results are robust without this restriction.

[1]We notice that the results of the paper hold with alternative weights, as the cross-sectional CPS weight and with an unweighted sample. Those additional results are available upon request.

1.1.2 Occupation definition

Worker We classify as a worker an individual who currently work in a paid job or who declares being temporarily absent from a paid job (EMPSTAT = $1, 10, 12$, and CLASSWKR = $20 : 28$).

Unemployed Individuals are classified as unemployed if they did not work for pay or profit and did not have a job from which they were briefly absent. The variable EMPSTAT = $20 : 22$ identifies unemployed individuals. We distinguish layoff unemployed persons when WHYUNEMP = 1,2 which record job loser/ on layoff and other job losers. All other unemployed individuals are considered not eligible for unemployment insurance. We further condition the *layoff* category with DURUNEMP, which allows us to further select groups of eligible UI claimants which respect to their unemployment duration. When studying the effect of regular UI benefits (Panel A), we define layoff individuals eligible for UI as those with less than 30 weeks of unemployment duration, which is the maximum regular US state UI duration. When considering UI extensions, we define a laid off unemployed agent as an unemployed individual with less than 99 weeks in unemployment. In a robustness check, we further restrict a *layoff* unemployed to declare having worked in the last twelve months (WNFTLOOK to be either 0 or 11). Robust are quite similar.

Entrepreneur and self-employed We define an entrepreneur as a self-employed (incorporated or unincorporated) worker (CLASSWKR = $10, 13, 14$), who currently work (EMPSTAT = $1, 10, 12$) and own his business (HHBUS = 1). Unfortunately, as compared to Cagetti and De Nardi (2006), we cannot control for an active management role in the CPS. We control business ownership by creating a specific variable that indicates whether or not the individual was owning his firm from 1994 to 2015, allowing us to control for measurement errors arising in the survey.[2] The share of entrepreneurs varies between 8.5% to 11% (relative to the population of workers, entrepreneurs, and unemployed) depending on the assumption considered (self-employment or entrepreneurship) and the period. With this restriction on business ownership, we might bias upward the actual number of entrepreneurs since some individuals might first engage in self-employment and then acquire a business. Moreover, HHBUS controls for business ownership within the family, as such we can not identify whether the individual is the owner of the family business or whether it is own by another member of the family. As our estimated share of entrepreneurs is close to the one estimated using the SCF (8-9%) we believe that our estimates are consistent.

[2]If we do not construct this additional variable, the flow from entrepreneurship to employment during a quarter jump to 16%, which is inconsistent with yearly flows. Therefore, our definition captures a part of self-employment that is not business ownership, but this is more consistent with resulting flows.

1.1.3 Summary statistics

Table 1 present the (unweighted) summary statistics of the sample of unemployed individuals from 1991 to 2010 and the main variables used throughout the empirical part.

Table. 1. Descriptive statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
AGE	39.3	12.4	20	28	49	65
Partner has a job	0.4	0.5	0	0	1	1
Average weekly wage	541.5	440.0	0.01	264.0	673.1	2,884.6
CPI adjusted weekly max benefits	424.9	114.2	212.8	346.9	492.2	963.4
Duration	38.9	31.9	0.0	16.0	53.0	119.0
Layoff def1	0.5	0.5	0	0	1	1
Layoff def2 (duration < 31 weeks)	0.4	0.5	0	0	1	1
State unemployment rate	6.5	2.2	2.1	4.9	7.9	14.6
$Max\ Regular_{weeks}$	25.9	1.4	12	26	26	30
$Max\ EB\ EUC_{weeks} + Max\ Regular_{weeks}$	46.3	26.8	14	26	70.5	99
	0.4	0.1	0.2	0.3	0.4	1.1
Hpi index	178.4	49.2	81.9	147.4	203.7	476.5
Log real GDP	10.8	0.2	10.3	10.7	10.9	12.1
Log per capita income	10.5	0.3	9.9	10.3	10.7	11.3

Note: this table show the main statistics of a sample of unemployed individuals from 1994 to 2015.

1.2 Exogeneity of regular UI benefit changes

We verify whether UI laws are correlated with determinants of the flows from unemployment to self-employment and entrepreneurship that could confound our estimates. Table 2 evaluate the determinants of state UI benefits with various state macroeconomic variables and union coverage, conditional on state and year fixed effects. We employ a similar set of determinants as in Hsu et al. (2018) and find no evidence of a relation over the period from 1994 to 2007. The estimated correlations are small and not statistically significant for the state unemployment rate, union coverage, housing HPI index, log real GDP per capita, average wage, log per capita income, and the UI trust fund reserves.

1.3 Cross-country evidence

In this section, we provide further empirical evidence on the mechanisms highlighted in the core paper. We update the cross-country evidence in Koellinger and Minniti (2009) to a much longer panel with more countries. We show that the fraction of nascent entrepreneurs in the economy is negatively correlated with higher UI generosity. We measure UI generosity as total government expenditure going to unemployment benefits (as a fraction of GDP) divided by one plus the unemployment rate, which translates the average UI spending of a country per unemployed individual. We measure the willingness to start a business as the fraction of nascent entrepreneurs from the Global Entrepreneurship Monitor (GEM) and an index of perceived opportunity measuring the percentage of 18-64 population (individuals involved in any

Table. 2. UI generosity and selection out of employment and entrepreneurship

	Total Max Regular$_{benefit}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate (%)	0.016							0.015
	(0.016)							(0.032)
log(Housing HPI index)		0.000						0.001
		(0.000)						(0.000)
log(real GDP per capita)			0.112					−0.038
			(0.250)					(0.243)
log(per capita income)				2.704				5.254
				(2.173)				(2.984)
Average wage					−0.002			−0.006
					(0.007)			(0.006)
Union Coverage						0.001		0.000
						(0.005)		(0.004)
UI trust fund reserves							0.012	−0.006
(% of covered wages)							(0.016)	(0.014)
State and year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.95
Observations	714	714	714	714	714	714	714	714

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard deviation clustered by state in parentheses. The measure of Total Max Regular$_{benefit}$ is in thousand of dollars.

stage of entrepreneurial activity excluded) who see good opportunities to start a firm in the area where they live. We build a panel dataset of 20 developed countries from 2001 to 2018 and regress the following specification:

$$\text{Entrepreneurship}_{it} = \beta \text{UI generosity index}_{it} + \delta \text{Unemp. rate}_{it} + \mathbf{X}_{it} + \mathrm{C}_i + \mathrm{Y}_t + u_{it}$$

where the measure of entrepreneurship is either perceived opportunity or nascent entrepreneurship, $\mathbf{X}_{it}$ is a vector of controls.[3] Those includes business taxes index and government program and support indexes toward entrepreneurs. All from the GEM data. C_i and Y_t define country and year fixed effects. Finally u_{it} is an error term. Table 3 show the results. Our results confirm the insight in Koellinger and Minniti (2009): nascent entrepreneurship is negatively correlated with UI generosity, a feature that our model reproduces well. Moreover, the share of individuals declaring that entrepreneurship is a good opportunity is significantly reduced with UI generosity.

[3]Perceived opportunity measure the percentage of 18-64 population (individuals involved in any stage of entrepreneurial activity excluded) who see good opportunities to start a firm in the area where they live.

Table. 3. Entrepreneurship and UI generosity

	TEA				Opportunity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UI index	-1.27^{**}	-1.10^{*}			-12.76^{***}	-12.46^{***}		
	(0.62)	(0.59)			(3.37)	(3.15)		
Replacement rate			-0.03	-0.02			-0.55^{**}	-0.55^{*}
			(0.03)	(0.03)			(0.26)	(0.30)
Unemployment rate	-1.99	0.68	-7.69	-5.93	-70.55^{***}	-80.91^{***}	-119.81^{***}	-123.90^{***}
	(8.38)	(7.79)	(5.47)	(5.74)	(24.60)	(26.61)	(24.16)	(25.70)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	267	232	264	229	267	232	264	229

Notes: *p<0.1; **p<0.05; ***p<0.01.

2 Model Appendix

2.1 Additional model validation

2.1.1 SCF sample

We use the SCF 2001, 2004, and 2007 waves in order to compute various moments relative to entrepreneurship. To be consistent with our CPS sample, we restrict the definition of an entrepreneur to individuals declaring being self-employed and owning a business (that they actively work in) with at least 5000$ of business capital. In table 4, we report those SCF moments that can be compared to those obtained with the model.[4]

Table. 4. Moments in different SCF waves and resulting moments in the baseline model.

Moment	SCF wave in				
	2001	2004	2007	*Data*	Model
Share of entrepreneurs (in %)	8.8	8.5	9.1	9.0	9.1
Fraction of unemployed (in %)	4.2	5.2	5.2	4.9	5.0
Ratio of median net worth (entrepreneur to worker)	7.3	8.7	7.5	7.8	8.1
Ratio of median net worth (entrepreneur to all population)	6.2	7.2	6.6	6.6	6.8
Ratio of median income (entrepreneur to worker)	1.71	1.67	1.57	1.65	1.66
Fraction of pop. with net worth < 1/10 of median (in %)	10	13	14	10	4
Gini coefficient - wealth	0.81	0.82	0.82	0.8	0.63
Gini coefficient - Entrepreneur's earnings	0.64	0.65	0.65	0.65	0.57
Fraction of capital hold by entrepreneurs (in %)	28.5	30	31.5	30-35	34
Ratio std. log earnings entrepreneurs to workers	1.3	3.83	1.71	?	2.1
Ratio of median entrepreneurs' debt to entrepreneurs' earnings	0.95	1.37	1.59	1.3	0.93
Ratio of median ent. income to ent. net worth (in %)	0.166	0.128	0.11	0.14	0.13
Ratio of median worker income to worker net worth (in %)	0.72	0.73	0.63	0.73	0.53

[4]The magnitude of the moments are quite similar under different assumptions for this value. We impose a restriction of 5000$ to reduce misreporting effects and to be more consistent with our CPS sample. Moreover, note that this definition of an entrepreneur selects individuals that are on average better off than the average of all self-employed.

2.1.2 Occupation flows by ability level

Figure 1 compare the shapes of the occupational flows in the model to their CPS counterparts. The flows are taken by educational attainment in the CPS data and ability levels θ are the model counterparts.[5] Note that the flows in and out of entrepreneurship are in general unchanged whether we define entrepreneurs as business owners or all self-employed individuals. The decreasing shape of the $W \rightarrow U$ flow is imposed with $\eta(\theta)$. While our calibration targets the *U-shape* of the $W \rightarrow E$ flow by earnings quantiles, we do no target it by ability and the latter relation is increasing both in the data and the model. All the other patterns are endogenously generated by the model and most of them are well-reproduced: we capture the decreasing pattern of the entrepreneurship to unemployment flow as well as the increasing shape of the reverse flow. We also capture the *hump-shape* of the $U \rightarrow W$ transition. Eventually, the flow shape the model captures the least is the *S-shape* from entrepreneurship to employment. We still capture the increasing part of this flow for HS to M groups but not the highly non-linear extremes.[6] In the model, highly-skilled entrepreneurs exit more often since corporate jobs are better outside opportunities without any business risk resulting in a higher incentive to search for a job.[7] Having a reasonably good fit of these flows in our baseline economy is an especially important premise since a key subject we will develop concern the effect of UI and its generosity on these flows.

2.2 Robustness and alternative specifications

In this section, we investigate alternative assumptions and specifications that potentially affect the conclusion of our main quantitative exercise.

2.2.1 Long-run elasticities of flows

We first provide the model estimates of the specification in equation (23) in the core of the paper when we use the resulting steady-state flows when computing the elasticity $\xi_{X,Y}$. The resulting elasticity of flows from insured unemployment to entrepreneurship is -0.245 while from insured unemployment to employment it is -0.167. The corresponding elasticity using flows

[5]Educational attainment is divided among $< HS$: less than a high school degree, H: high school degree, $< C$: some college but no degree, B: bachelor's degree, M: master's degree, $> C$: higher college and professional school degrees. Matching ability groups with education groups is a subject of discussion. There is a caveat: the CPS data do not provide any information about wealth or business earnings and unemployment compensation. The included family income variable is rather imprecise and its range is too small. Education is the best directly available element comparable to the model. However, we still tried to match by indirect means: in a supplementary appendix available upon request, we report flows by *reconstructed wages* using a fitted wage that takes into account age, education, etc.

[6]According to the BLS, groups $> C$ and $< HS$ together represent fewer than 15% of the working population.

[7]In the online appendix section A, we show that this *S-shape* becomes a hump-shaped curve at a yearly frequency for self-employed business owners. At the higher bi-monthly frequency, we might capture movements that may mainly concern the lowest educated group potentially running more unstable businesses in the short-run.

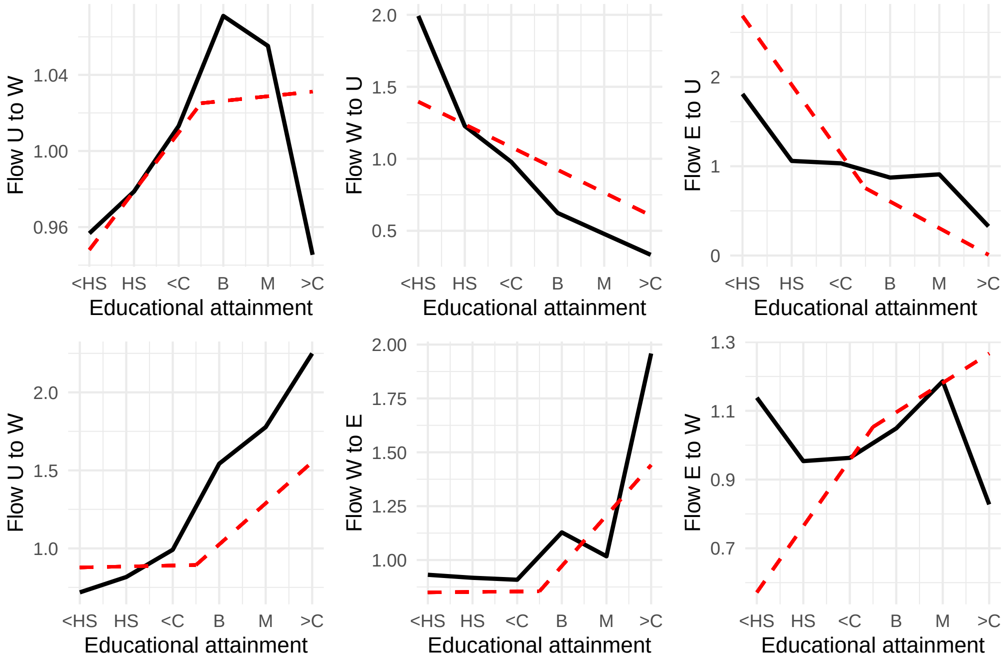


Figure 1. Mean two months occupational flows by CPS educational attainment (black, top horizontal axis) and model ability level θ (red, 3 values order by θ_1,θ_2,θ_3). The solid lines refer to self-employed business owners. Legend: U: unemployment, W: employment, E: entrepreneurship. *Data sources:* authors' own computations using CPS data from 1997 to 2017.

from the initial steady-state distribution are $\xi_{U^I \to E}$ =-0.287 and $\xi_{U^I \to W}$ =-0.172. This means that there are not substantial composition effects among the population of insured unemployment after having implemented the policy change.

2.2.2 Source of UI generosity: UI duration versus UI benefit amount

UI generosity is contingent on the level of UI benefits or their duration. In section 5.1.1 of the core paper, our metric of UI generosity did not explicitly specify the origin of a variation in UI generosity. We run a robustness exercise to investigate the impact on occupational flows and masses when UI generosity is due only to a variation of the UI replacement rate or due only to a variation in UI duration. Table 5 displays the results of this exercise. Overall, whether we increase the level of UI benefits or the duration, we find that the measured flows and masses respond qualitatively the same as our elasticities in the core paper. Differences in magnitudes are explained by the fact that a variation in the level of UI benefits is not directly comparable to a variation of the duration. The former acts directly on the entire path of UI benefits while the latter increases the number of periods of total UI claims. Whether it is better to implement a change in UI generosity through higher replacements rates or higher UI durations is a policy question out of the scope of the current investigation.

Interestingly, results from our empirical appendix also indicate a similar discrepancy between UI benefits and UI duration. Increasing UI duration is shown to impact less the flow from unemployment to self-employment, consistently with the model. Finally, when the UI duration is relatively low (around 20 weeks of duration), the effect of increasing UI benefits turn out to be small for the flow from unemployment to employment (an elasticity of around -0.09 against -0.17 in the benchmark.). Again, this is consistent with the result in our main empirical appendix: when considering variations in regular benefits, we find no statistically significant effects on the flow from unemployment to employment.

Table. 5. Elasticity of insured unemployment and long-run occupation masses to UI generosity

	Insured U flow to		Long-run mass of		
	Entrep.	Paid Emp.	Unemp.	Entrep.	Paid Emp.
Elasticity to UI benefit level	-0.42^{***}	-0.31^{***}	0.17^{***}	-0.22^{***}	0.01^{***}
Elasticity to UI duration	-0.27^{***}	-0.15^{***}	0.11^{***}	-0.07^{***}	0.00

Note: *p<0.1; **p<0.05; ***p<0.01.

2.3 Additional Robustness

We run two additional robustness checks that we believe might influence the main message of the paper that the UI has important effects on the selection into entrepreneurship. We first verify if including a form of learning changes the results. Indeed, learning can be an important part of the business prospect that can not be well captured by our endogenous business search s_e. Second, we check whether our results hold with tighter labor market frictions.

2.3.1 Business Maturity and Learning

In this alternative specification, we assume that upon entry, entrepreneurs face a higher probability to start with a low shock z. This aims to capture a form of learning about the demand the time needed to accumulate goodwill, client lists, or customer base. We assume that new entrants draw their productivity from the distribution $z \sim \mathcal{H}(z)$ with $Q(z) \leq \mathcal{H}(z)$, $(\forall z)$ where $Q(z)$ defines the probability distribution of z of new entrants in the baseline model. This condition states that new entrants start with, on average, a lower business productivity, and then evolve over-time according to the AR(1) described in the baseline model.[8] By sake of parsimony, we assume $\mathcal{H}(z)$ shifts the mean of the $Q(z)$ distribution over the possible discretized values of z by 10%. Under this new specification, we calibrate again the model to match targeted moments. Table 6 shows that our results remain valid under this specification, with an increase in the adverse effect of UI on the propensity to start a business due to the additional risk generated by the learning profile.

[8] A similar learning/maturity process is used in Clementi and Palazzo (2016) to give a role to the age of the firm.

Table. 6. Elasticity of insured unemployment to UI generosity with/without learning

	Elasticity to UI			
	$U_I \rightarrow E$	$U_N \rightarrow E$	$U_I \rightarrow W$	$U_N \rightarrow W$
1. Benchmark	-0.287^{***}	-0.015^{***}	-0.167^{***}	0.002^{***}
2. With learning [a]	-0.331^{***}	-0.015^{***}	-0.171^{***}	0.002^{***}

Note: *p<0.1; **p<0.05; ***p<0.01. [a] recalibrated to match key moments.

2.3.2 Higher labor market frictions

The last experiment we perform is to check the sensitivity of our results with relatively more frictional labor market. To do so, we increase the worker firing rate by 1pp for each ability level and decrease the job and business finding rate by 3pp. The corresponding new stationary equilibrium displays a higher unemployment rate of 6.8%. Under this new calibration, the main results of the paper are qualitatively similar: higher insurance significantly dampens the propensity of unemployed workers to select into entrepreneurship, and reallocate the labor force to employment activities. The elasticity of unemployment flow to entrepreneurship is close to the benchmark economy, of about -0.312. This slight increase is due to the higher frictions in the labor market: when employment is riskier, increasing unemployment insurance lead unemployed individuals to search for employment, and less so for starting a self-employment business.

3 Numerical implementation

State space and grid definition In our model, an household is fully characterized by a state vector $\mathbf{x} = (o, y, \theta, z, j, a)$ with $a \in A$, $y \in \mathcal{Y}$, $z \in \mathcal{Z}$, $\theta \in \Theta$, $o \in \{w, e, u\}$ and $j = J$. We compute the household problem using a grid of asset $\mathbf{a}$ of 350 points (adding more points only very marginally increase our accuracy), spaced according to an exponential rule. We discretize the process z, y and θ with respectively 7, 5 and 3 grid points.

3.1 Algorithm

We organize the algorithm as follows.

1. Initialize a full dimension grid space composed of all different possible asset values (a), productivity level (y), innate ability (θ) and entrepreneurial state (z). The maximum asset level is chosen sufficiently large to place the policy functions in an ergodic set.

2. Guess initial tax rate τ_w and prices $\{w, r\}$.

3. Given prices, solve the consumption-saving-search (CSS) problem, productive capital k, and search efforts of an agent. We use the DC-EGM algorithm of Iskhakov et al. (2017)

for the CSS problem.

4. Construct the transition matrix $\mathbf{M}$ generated by Π_y, Π_z and Π_θ, $a'(\mathbf{x})$, $s_w(\mathbf{x})$, $s_e(\mathbf{x})$. Compute the associated stationary measure of individuals $\Gamma(\mathbf{x})$, by first guessing an initial mass of one of households with zero asset and then by iterating on $\Gamma'(\mathbf{x}) = \mathbf{M}\Gamma(\mathbf{x})$ until $|\Gamma'(\mathbf{x}) - \Gamma(\mathbf{x})| < \mu$, with μ very small.

5. Compute the resulting total asset level, total labor supplied and total investment in the entrepreneurial sector. Total capital invested in the corporate sector is given as the difference between total savings and total capital invested in the entrepreneurial sector. Total labor used in the corporate sector is given by total labor supplied by workers.

6. Update prices $\{r, w\}$ using the marginal productivities in the corporate sector and tax rate τ_w to close the government budget up to a relaxation. Back to step 2 until convergence of labor income tax rate and prices.

3.2 Transitional dynamics

To solve the transition, we compute the solutions of the household problem backward, starting at the new steady-state. We then find prices that are consistent with the implied policies and we iterate until convergence. We assume that the economy is in the initial steady-state in period 0 and the reform is announced and implemented in period 1. Agents did not anticipate the policy before its implementation. The economy makes a transition to reach the final steady-state in period T. We choose T large enough so that the resulting stationary distribution in period T is close enough to the final steady-state equilibrium. The algorithm for the transition dynamics is:

1. Guess a path for $\{\mathcal{L}_1, ..., \mathcal{L}_{T-1}\}$ with $\mathcal{L}_t = \{r_t, w_t, \tau_{w,t}\}$. $\mathcal{L}_0$ and $\mathcal{L}_T$ are given by initial and final steady-states.

2. Use value functions of the final steady-state (period T) to solve the households' problem backward starting from $T-1$ until period 1.

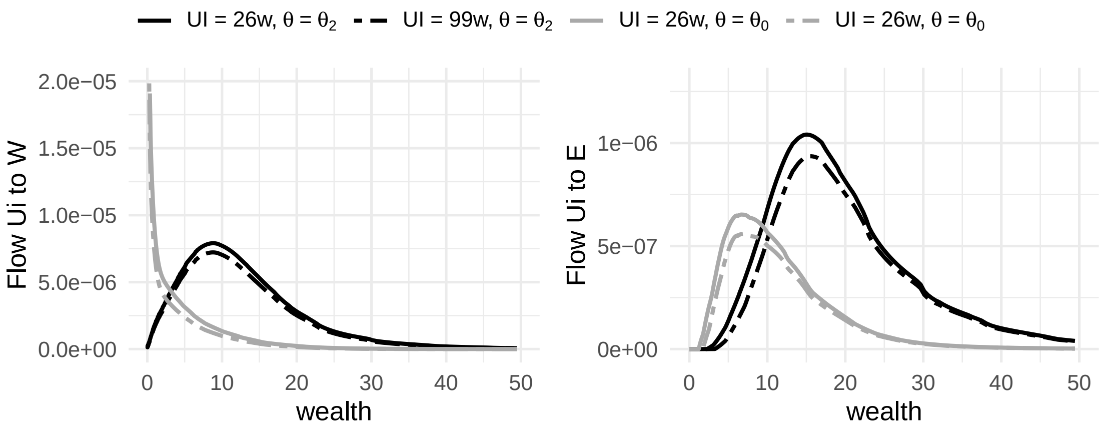
3. Use the distribution of the initial steady-state and the resulting policy functions to compute the path of the distribution of household $\{\hat{\Gamma}(\mathbf{x})_1, ..., \hat{\Gamma}(\mathbf{x})_T\}$.

4. Given these distributions, compute new path $\{\mathcal{L}_1, ..., \mathcal{L}_{T-1}\}$. Iterate from step 2 until the difference between the initial path is close enough to the resulting path.

5. When convergence is achieved, check if the resulting final distribution $\hat{\Gamma}(\mathbf{x})_T$ is close enough to the steady-state distribution $\Gamma(\mathbf{x})_T$ up to a relaxation. If the two distributions are identical, then stop, else, increase the number of periods T.

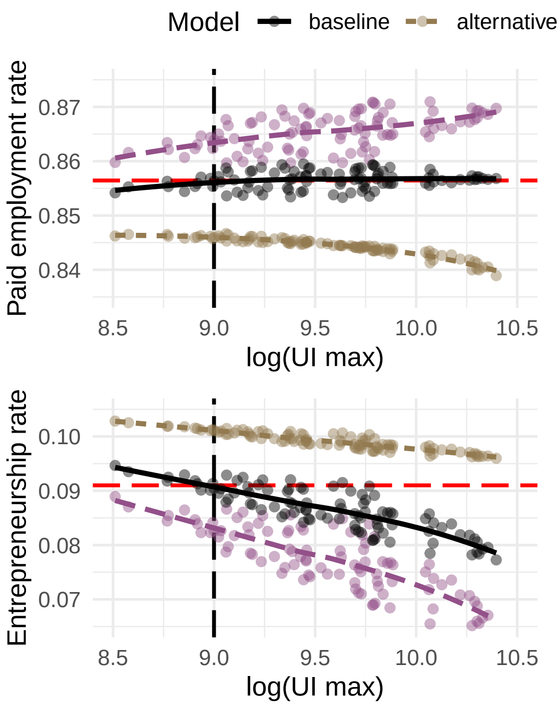
3.3 Additional figures

Figure 2. Model flows from insured unemployment to entrepreneurship.



Note: we display the flows out of insured unemployment with $j = \bar{J}$ for two models with the same benchmark initial distribution: the baseline with $\bar{J} = 26$ weeks (solid line) and an alternative with $\bar{J} = 99$ weeks (dashed line).

Figure 3. Effect of alternative tax scheme on occupation masses.



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