Gross Labor Market Flows and Entrepreneurship

Online Appendix

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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 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. 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 for 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.

1.1.2 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 Agents 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

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

WHYUNEMP = 1,2 which records 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 with 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 agents as unemployed individuals 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 In the core of the paper, we define an entrepreneur as a self-employed worker (CLASSWKR = $10, 13, 14$), who currently work (EMPSTAT = $1, 10, 12$). We additionally control in a robustness check for self-employed individuals who own their business (HHBUS = 1).[2] The share of entrepreneurs varies between 8.5% to 12% (relative to the population of workers, entrepreneurs, and unemployed) depending on the assumption considered (self-employment or self-employed business owners) and the period. With the 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 owned by another member of the family. As our estimated share of entrepreneurs defined as self-employed individuals or self-employed business owners are close to their counterparts in the SCF, respectively 8-9% and 10.5-12%, we believe that our CPS estimates are consistent.

1.1.3 Summary statistics

Table 1 present the (unweighted) summary statistics of the sample of unemployed individuals from 1994 to 2015 and the main variables used throughout the empirical part.

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

[2] We control business ownership by creating a specific variable that indicates whether or not the individual owned his firm from 1994 to 2015, allowing us to control for measurement errors arising in the survey. 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.

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.

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.

Table. 2. Regular UI benefits and aggregate economic variables

	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.

1.3 Cross-country evidence

In this section, we provide further empirical evidence on the mechanisms highlighted in the core of the 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 years old population (individuals involved in any 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. These include business taxes index, government program and support indexes toward entrepreneurs. All controls are from the GEM data. C_i and Y_t define country and year fixed effects. Finally u_{it} is an error term. Table 3 displays 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.

Table. 3. Entrepreneurship and UI generosity

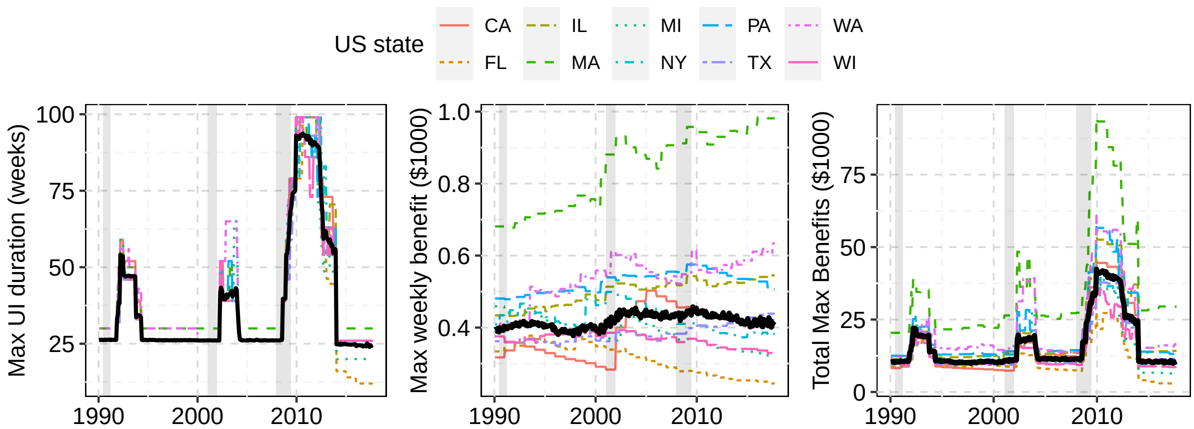
	TEA				Opportunity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UI index	-1.27^{**}	-1.10^{*}			-12.76^{***}	-12.46^{***}		
	(0.62)	(0.59)			(3.37)	(3.15)		
Replacement rate			-0.03	-0.02			-0.55^{**}	-0.55^{*}
			(0.03)	(0.03)			(0.26)	(0.30)
Unemployment rate	-1.99	0.68	-7.69	-5.93	-70.55^{***}	-80.91^{***}	-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.

1.3.1 UI weekly benefit amount and maximum duration

We obtain data for regular UI duration and the maximum weekly benefit amount at the state level from the US department of labor's "significant provisions of state unemployment insurance laws". Data for UI extensions comes from Farber et al. (2015) complemented with the EUC91 extensions. Figure 1 displays the maximum duration ($Max\ Regular\ Weeks_{st} + Max\ EB\ EUC\ Weeks_{st}$), the maximum weekly benefit amount ($Max\ WBA_{st}$), and maximum claimable extended benefits ($Max\ Extended\ UI_{st}$), both as the US average and for selected states.

Figure 1. Maximum UI benefits duration and amount: US average and selected states



Left panel: maximum duration ($Max\ Regular\ Weeks_{st} + Max\ EB\ EUC\ Weeks_{st}$). Middle panel: maximum weekly benefit ($Max\ WBA_{st}$), CPI adjusted. Right panel: total claimable benefits ($Max\ Extended\ UI_{st}$), CPI adjusted. The black line is the US average. Grey areas reports NBER recessions.
Sources: US Department of Labor, significant provisions of state unemployment insurance laws biannual reports.

1.3.2 SIPP transitions

The SIPP data (1996:2008) are detailed in the core of the paper. We just describe here the corresponding quarterly flows between occupations in Table 4. As mentioned in Krusell et al. (2017) there are large discrepancy between SIPP and CPS flows, most notably concerning flows from entrepreneurship to unemployment and from employment to unemployment. Moreover, there is a lower share of unemployed individuals in the SIPP relative to the CPS. All other flows are close to the CPS estimate, as shown in Table 1 (core paper).

Table. 4. Aggregate quarterly occupational gross flows rate in the SIPP.

	Gross flow (%) to			**Masses** (%)
From	*Employment*	*Entrepreneurship*	*Unemployment*	
Employment	98.37	0.67	0.96	84.8
Entrepreneurship	6.48	93.16	0.36	10.6
Unemployment	43.37	2.23	54.40	4.6

Source: authors' computations using SIPP data from 1996:2008. We restrict our sample to individuals between the ages 20 to 65 years old.

2 Model Appendix

2.1 Robustness and alternative specifications

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

2.1.1 Long-run elasticities of flows

We first provide the model estimates of the specification in equation (18) 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 -0.25 while from insured unemployment to employment it is -0.05. This means that there are not substantial composition effects among the insured unemployment population after having implemented the policy change.

2.2 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.

2.2.1 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.[3] For the 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 5 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.

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

Table. 5. Elasticity of insured unemployment to UI generosity with/without learning

	Elasticity to UI			
	$U_I \to E$	$U_N \to E$	$U_I \to W$	$U_N \to W$
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.

2.2.2 Higher labor market frictions

The last experiment we perform is to check the sensitivity of our results with a relatively more frictional labor market. To this end, we increase the worker firing rate by 1 percentage point for each ability level and decrease the job and business finding rate by 3 percentage points. 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 agents to select into entrepreneurship, and reallocate the labor force to employment activities. The elasticity of the flow from unemployment to entrepreneurship, at about -0.312, is close to that in the benchmark economy. The slight increase is due to higher frictions in the labor market: when employment is riskier, increasing unemployment insurance leads unemployed individuals to search for employment and decreases the search to start a self-employed 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 **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.

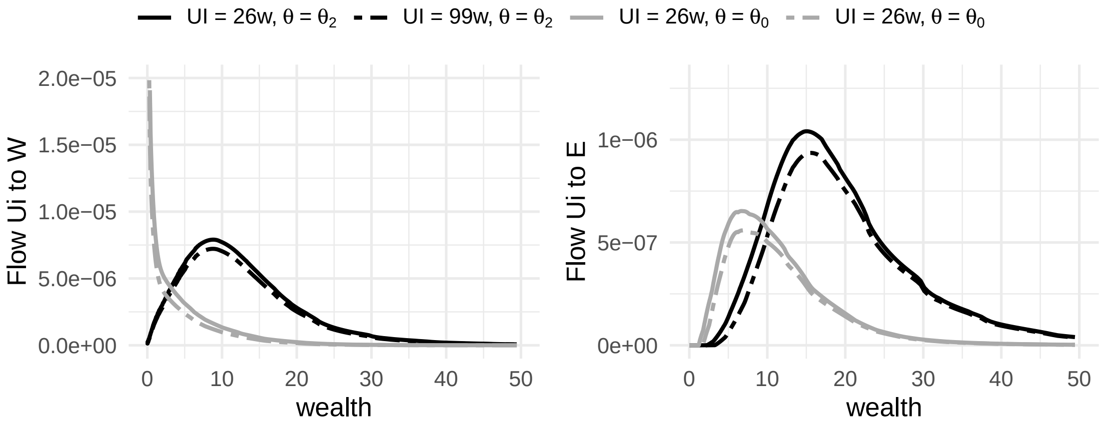
3. Use the distribution of the initial steady-state and the resulting policy functions to compute the path of the distribution of household $\{\hat{\Gamma}(\mathbf{x})_1, ..., \hat{\Gamma}(\mathbf{x})_T\}$.

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.

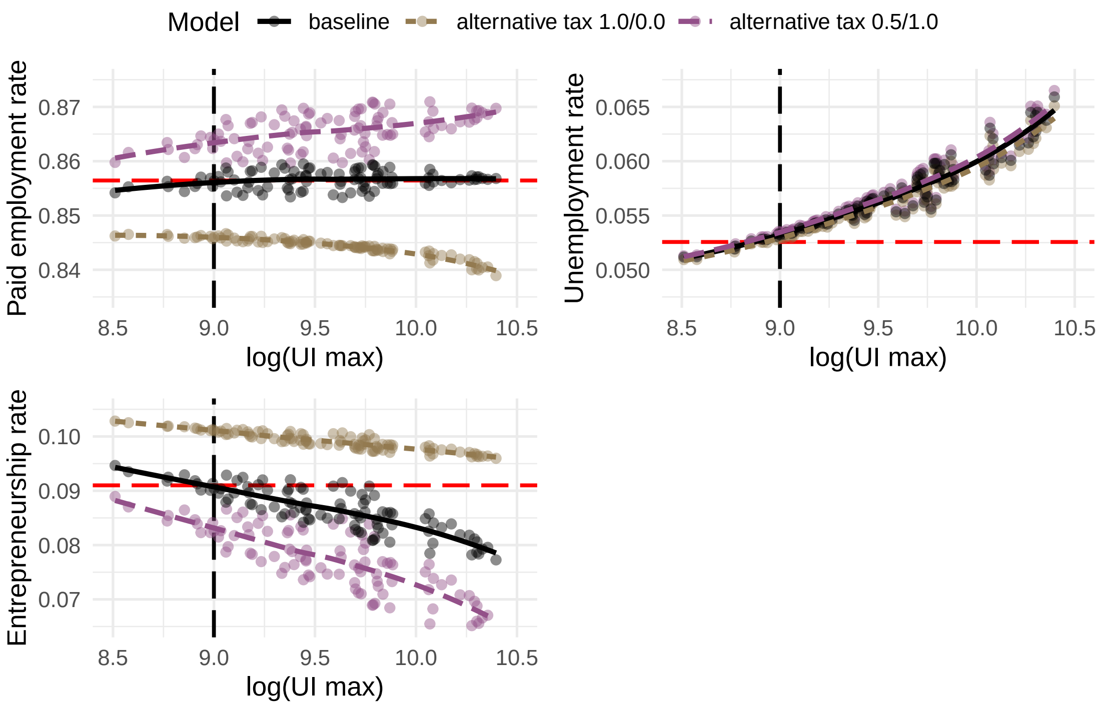
3.3 Additional figures

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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