Gross Labor Market Flows and Entrepreneurship*

Alexandre Gaillard†
Toulouse School of Economics

Sumudu Kankanamge‡
Toulouse School of Economics

First version: September 2018.

This draft: June 2021.

Abstract

We introduce an occupational choice model accounting for US gross flows across employment, unemployment, and entrepreneurship and assess their responsiveness to labor market policy changes. Search frictions over all three occupations and a technology letting entrepreneurs produce with their own labor, business capital, or both, are key in generating the observed aggregate gross flows and along the wealth and ability dimensions. Responsiveness of flows to variations in unemployment insurance generosity are aligned with empirical estimates, with changes in the relative riskiness of occupations playing a significant role. In turn, large reallocations between entrepreneurship and employment appear, shaping aggregate occupational shares.

Keywords: Entrepreneurship, Occupational Choice, Labor Market Mobility, Unemployment Insurance.

JEL classification: E23, E24, J62, J65.

*We are especially grateful to Christian Hellwig for his many helpful comments. We are indebted in no specific order to Arpad Abraham, Mark Bils, Fabrice Collard, Patrick Fêve, Eugenia Gonzalez-Aguado, Dirk Krueger, Tim Lee, Benjamin Moll, Franck Portier, and José Víctor Ríos Rull for their useful comments and discussions. We are also very grateful for constructive comments from participants at the 2017 SED in Edinburgh, the XXII Workshop on Dynamic Macroeconomics in Vigo, the 23rd CEF conference in New York, the 22nd T2M conference in Paris, the 2018 Spring Midwest Macroeconomics Meetings in Madison, the 2018 ESEM in Cologne, the ADEMU conferences in Toulouse (TSE) and Prague (CERGE-EI), and the 2019 Transpyrenean Macro Workshop. This paper supersedes a previous version titled "Insuring Entrepreneurial Downside Risk". The authors are solely responsible for any remaining errors or omissions. The authors acknowledge funding from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program) and from Banque de France.

†Email: alexandre.gaillard@tse-fr.eu. Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France.

‡Email: sumudu.kankanamge@tse-fr.eu. Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France.

1 Introduction

To the extent that we consider the pool of all self-employed individuals, entrepreneurs represent 10% to 12.5% of the US labor market and, in the data, the gross flows in and out of this occupation significantly contribute to the dynamics of this market.[1] Each quarter, 3.6% of the unemployed population and 0.7% of the employed become entrepreneurs such that the former account for 20% of the individuals transiting into entrepreneurship. Conversely, turnover among entrepreneurs is large: every quarter, 6.3% of this pool turns to employment while 1.45% become unemployed. Nevertheless, the contribution of entrepreneurship to the gross flow dynamics and the responsiveness of these flows to labor market policy changes have received little attention so far. This paper builds a parsimonious occupational choice model of the US labor market and assesses its ability to account for two key empirical facts: the micro and macro-level patterns of gross labor market flows across employment, unemployment, and entrepreneurship and their observed responsiveness to well-documented adjustments in the labor market: unemployment insurance (UI) generosity revisions.

Our model combines two families of models widely used in the literature: search models in the spirit of Mortensen and Pissarides (1994) and occupational choice models with entrepreneurs as pioneered by Quadrini (2000) and Cagetti and De Nardi (2006). In the former class of models, labor market frictions are the main determinants of gross flows in and out of unemployment while self-employment is rarely distinguished from employment. Moreover, these models ignore in general the importance of wealth and associated occupational risks in guiding microeconomic occupational decisions.[2] In a recent contribution, Krusell et al. (2017) demonstrate the importance of wealth effects in replicating gross flows in and out of the labor force while the liquidity effect studied in Browning and Crossley (2001) and Chetty (2008) illustrate how individual wealth determines the reactivity of flows to the UI policy. In contrast, in the occupational choice family of models, wealth is a key component that conditions the decision to select into entrepreneurship. However, in the presence of a collateral constraint on business capital, only sufficiently wealthy individuals set up a firm under the typical use of a Cobb-Douglas entrepreneurial technology or when business capital is used as the sole produc-

[1] Cagetti and De Nardi (2006) provide a meticulous overview of the different definitions of entrepreneurship used in the literature. Given our focus on labor market flows and on the occupational decisions to start a business out of unemployment and employment, it is empirically relevant to consider all self-employed individuals contributing to the labor market dynamics. The reported numbers are from the CPS (1995:2015).

[2] See Wasmer and Weil (2004) for an extension of the Diamond-Mortensen-Pissarides framework with a role for financial funding on the entrepreneurial side and Krusell et al. (2010) for the consideration of precautionary savings in this setting.

tion factor. Consequently, in these models, it is often the case that almost no individual selects into entrepreneurship below the median wealth level. This is at odds with the empirical evidence where an important fraction of new self-employed individuals establishes businesses with close to no capital.[3] In the end, the two strands of the literature provide channels to describe gross labor market flows, but, taken separately, they are unable to produce an accurate characterization of these flows nor the micro-level decisions to change occupations.

We build on the above two classes of models and introduce a number of mechanisms to better account for the gross labor market flows. We use an incomplete markets setting with labor market frictions and idiosyncratic shocks where households can endogenously choose between employment, unemployment, and entrepreneurship. Employed individuals are subject to an exit risk, either due to a voluntary action or a layoff, while adverse shocks may compel entrepreneurs to cease their businesses. Unemployed agents face a standard job search friction. This friction is extended to entrepreneurs that can search *on-the-business* for a job. We introduce an additional search friction to rationalize the time and effort necessary to set up a new business. As a consequence, unemployed individuals have to search for a business idea before becoming entrepreneurs and workers may do the same *on-the-job*. These frictions are key in generating consistent gross flows across the three occupations. Importantly, we introduce a flexible entrepreneurial production function: we let self-employed individuals produce without capital by using their own labor supply. Because of the perfect substitutability between the own labor of entrepreneurs and business capital, this technology considerably improves the fitting of the data by letting wealth-poor individuals select into self-employment. This technology is also consistent with our definition of entrepreneurship by taking into account both smaller activities, using mostly self-employed labor and larger businesses, with significant levels of entrepreneurial capital. The first key contribution of this paper is to show that our model produces an accurate characterization of the US gross labor market flows across employment, unemployment, and entrepreneurship along three dimensions: at the aggregate level with respect to the Current Population Survey (CPS) counterparts, at the micro-level by wealth quantiles with respect to the Survey of Income and Program Participation (SIPP) data, and by ability as proxied by education levels in the CPS. To the best of our knowledge, no previous model of gross labor market flows achieved this result in an entrepreneurial context.

[3] We use the panel data in the Survey of Income and Program Participation (SIPP) to document this fact. Consistent with our setup, Hurst and Lusardi (2004) estimate the role of wealth in the selection into entrepreneurship (defined as business ownership) and find a mild effect except at the top of the wealth distribution.

Our second contribution is to assess whether the model is consistent with the responsiveness of occupational choices and the resulting gross flows to a change in labor market policy. We focus on an empirically measurable alteration of the labor market: revisions to the UI system generosity (defined as the product between the level of benefits and coverage duration). This is of particular relevance, as Røed and Skogstrøm (2014) and Hombert et al. (2020) point out the substantial interactions between UI generosity and the selection into entrepreneurship.

We first estimate the effect of a change in UI generosity on the resulting occupational choices by comparing two groups: the insured unemployed group, eligible following a layoff and the uninsured group, non-eligible for UI. Our empirical study uses the 1994–2015 CPS micro-data and the variation in regular and extended UI benefits – from the Extended Benefits (EB) program and the successive Emergency Unemployment Compensation (EUC) programs – across US states and over time.[4] A more generous UI program significantly changes occupational choices and thus gross flows. Notably, the propensity to select into entrepreneurship is significantly reduced: a standard deviation increase in UI generosity corresponds to a 7.4% decline in the likelihood of a transition from unemployment to entrepreneurship.

Second, we assess the responsiveness of the gross flows to UI variations within our model. Our setting features a rich characterization of the US UI system with a detailed accounting of benefit caps, replacement rates, and UI durations. Importantly and consistent with the UI system in place in the US and many other countries, self-employed individuals are not covered by UI. We use a counterfactual experiments framework to measure the responsiveness of gross flows: in a nutshell, we run the model to generate an extensive variety of UI generosity situations that matches the empirical variety across US states and over time. This framework then lets us capture key insights about the effects of varying UI generosity and the sizable repercussions on gross occupational flows, occupational masses, and aggregate outcomes. We establish that the model produces gross flow elasticities comparable to the data. We find that the elasticity to UI generosity of the flow from the insured unemployed pool to entrepreneurship is negative and about five to six times higher than the corresponding elasticity of the flow to the employment pool. Intuitively, an increase in UI generosity improves the direct and indirect insurance levels of both the employment and unemployment occupations while the entrepreneurial occupation is mostly unaffected. Moreover, the responsiveness displays a

[4] Our approach shares some similarities with the recent literature exploring the effects of UI generosity beyond direct effects on the decision to exit unemployment (Rothstein, 2011; Farber et al., 2015). In a different context, Hsu et al. (2018) show that UI affects the proportion of foreclosures in housing markets and Agrawal and Matsa (2013) show that it affects corporate financing decisions.

large heterogeneity among households. Focusing on gross flows from insured unemployment to self-employment, wealth-poor and low-ability individuals react the most to a change in UI generosity. In the model, the profitability of many businesses is still scaled to personal wealth making the occupational decision of wealth-poor individuals more sensitive. We also show that adding even a simple form of monitoring of the job search effort of unemployed agents improves the above responsiveness with respect to the data.

Furthermore, the model establishes that flows into and out of entrepreneurship play a significant role in shaping the aggregate occupational masses. In substance, when UI generosity increases, the occupational flow from entrepreneurship to employment increases while the opposite flow decreases because of the change in the relative risk (or insurance value) between those two occupations. Because the masses of employed agents and entrepreneurs are larger than the mass of insured unemployed agents, the reallocation from entrepreneurship to employment is a key factor in counterbalancing the flow out of insured unemployment. As a result, our model generates an empirically consistent stable to slightly increasing mass of employed individuals, an increasing mass of unemployed individuals, and a decreasing mass of entrepreneurs when UI generosity increases. Our approach, thus, gives an additional perspective to the UI literature. On the one hand, UI generosity has a significant impact on optimal individual decisions and labor market flows, especially the depressing effect on the incentive to exit unemployment (Moffitt, 1985; Meyer, 1990; Chetty, 2008). On the other hand, as empirically established by Chodorow-Reich et al. (2019) and Boone et al. (Forthcoming), the effect of UI generosity on the aggregate level of employment is small or non-significant. Our framework produces a consistent gross flow mechanism to reconcile those views by accounting for the self-employment margin. Overall, an important conclusion of our responsiveness exercise is that asymmetric labor market policies, such as the coverage of UI, significantly change the trade-off between occupations and, in turn, the resulting gross flows.

Finally, we use our framework to study the changes in occupational masses during the Great Recession, taking into account the various UI extensions that were implemented. We target some of the changes in the observed gross flows and find that the model performs well over the remaining occupational flows and the responses of occupational masses during this period. A decomposition of the effects reveals that the impact of UI extensions on the propensity to select into entrepreneurship was large and generated a persistent 0.4-0.45 percentage point drop in the share of entrepreneurs in the economy.

The remaining of the paper is organized as follows. Section 2 introduces our model and its parameterization. Section 3 reports the performance of our model in producing consistent gross labor market flows and Section 4 discusses the responsiveness of the model to changes in UI generosity. Section 5 recounts our Great Recession experiment and Section 6 concludes.

2 A Model of Gross Labor Market Flows with Entrepreneurship

In this section, we develop an incomplete markets dynamic general equilibrium model of entrepreneurship with occupational choices and search frictions. A unit measure of *ex-post* heterogeneous agents can be either employed, entrepreneurs, or unemployed. Entrepreneurs hold small businesses and together with a representative corporate firms sector provide the production of the economy. The model parsimoniously characterizes average aggregate gross labor market flows across the above three occupations while still generating empirically consistent micro-level behaviors. We also incorporate an extensive depiction of the UI system in the US to let us measure the responsiveness of flows to UI changes.

2.1 Households

The economy is populated by a continuum of infinitely-lived households of measure one. Every period, each agent falls in one of three occupations $o_t \in \mathcal{O} \equiv \{e, w, u\}$: entrepreneurship ($e$), employment ($w$), or unemployment ($u$). We keep using the $\{E,\ W,\ U\}$ notations to designate respectively entrepreneurs, workers and unemployed individuals. All individuals are described, among other things, with an ability component $\vartheta \in \Theta$ and savings $a_t \in \mathcal{A}$. r_t and w_t are respectively the interest rate on savings and the wage rate in the economy.

Life-time utility is derived from consumption c_t and disutility from search:

$$\mathcal{U}_t = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(c_t, s_{e,t}, s_{w,t}) \right], \tag{1}$$

where $s_{e,t}$ and $s_{w,t}$ are the search efforts exerted to respectively start a business and find a new job. β is the discount factor. In the following, we drop the time index t unless necessary. Labor is supplied inelastically and the utility function is:

$$u(c, s_e, s_w) = \frac{c^{1-\sigma} - 1}{1-\sigma} - \left(s_w^{\psi} + s_e^{\psi} \right)^{\phi/\psi}, \tag{2}$$

with ψ and ϕ the search elasticities. Note that if $\phi = \psi$, the utility is separable in s_e and s_w.

The labor income of a working household, the replacement income of an unemployed individual, and the business income of an entrepreneurial household all depend on ability ϑ. This component follows the process: $log(\vartheta) = \rho_\vartheta \log(\vartheta_{-1}) + \epsilon_\vartheta$, with $\epsilon_\vartheta \sim \mathcal{N}(0, \sigma_\vartheta)$ and the invariant distribution Π_ϑ.[5]

Workers are subject to an additional persistent idiosyncratic shock y on their labor income that we call *match-quality*.[6] It follows the process: $\log(y) = \rho_y \log(y_{-1}) + \epsilon_y$, with $\epsilon_y \sim \mathcal{N}(0, \sigma_y)$. For a new worker, this shock is drawn from the invariant distribution Π_y. Finally, entrepreneurs face a persistent idiosyncratic business shock z following the process: $log(z) = \rho_z log(z_{-1}) + \epsilon_z$, with $\epsilon_z \sim \mathcal{N}(0, \sigma_z)$. A new entrepreneur draws her initial business shock in the invariant distribution Π_z. All processes are discretized into Markov chains with support $\vartheta \in \Theta \equiv \{\vartheta_1, ..., \vartheta_T\}$, $y \in \mathrm{Y} \equiv \{y_1, ...y_Y\}$, and $z \in \mathcal{Z} \equiv \{z_1, ..., z_Z\}$.

With j the unemployment insurance status, the value function of a worker is $W(\mathbf{x}_w, j)$ with state vector $(\mathbf{x}_w, j) \in \mathbb{X}^w \times \mathcal{J}$ and $\mathbf{x}_w \equiv (a, \vartheta, y) \in \mathbb{X}^w \equiv \mathcal{A} \times \Theta \times \mathrm{Y}$. An entrepreneur has the value function $E(\mathbf{x}_e, j)$ with state vector $(\mathbf{x}_e, j) \in \mathbb{X}^e \times \mathcal{J}$ and $\mathbf{x}_e \equiv (a, \vartheta, z) \in \mathbb{X}^e \equiv \mathcal{A} \times \Theta \times \mathcal{Z}$. An unemployed individual has the value function $U(\mathbf{x}_u, j)$ with state vector $(\mathbf{x}_u, j) \in \mathbb{X}^u \times \mathcal{J}$ and $\mathbf{x}_u \equiv (a, \vartheta) \in \mathbb{X}^u \equiv \mathcal{A} \times \Theta$.

2.1.1 Workers

Workers earn labor income $h(\vartheta)yw$, where the function $h : \vartheta \mapsto \mathbb{R}$ maps their individual ability ϑ into a working ability. They have a probability $\eta = \eta(\vartheta)$ of being fired due to no fault of their own and a probability q of voluntarily quitting their job. Only in the former case, do they face insured unemployment and can expect to get continuation value $U(\mathbf{x}'_u, J)$.[7] By providing effort s_e, workers can search for business ideas *on-the-job* and start a business in the next period with probability $\pi_e(s_e)$. Business search effort can describe market research on the feasibility of an idea, competition assessment, business education, agency costs or the time needed to fill administrative forms, validate product norms, etc. They then voluntarily change their occupation, loose their UI rights and can expect a continuation value $E(\mathbf{x}'_e, 0)$.

[5]Ability can change over time in order to generate additional saving motives as our model abstracts from life-cycle aspects, human capital or health risks which can explain a large productivity dispersion in the data.

[6]This model does not include an explicit matching process but y can be viewed as a match-quality component because it starts and ends with a specific job while not appearing as a state for the unemployed or the entrepreneur. This process brings our generated distributions and transitional flows closer to the data.

[7]Notice that in the model, $U(\mathbf{x}_u, j) < W(\mathbf{x}_w)$, $\forall (\mathbf{x}_u, \mathbf{x}_w, j)$. Therefore, we rule out any voluntary transition to unemployment. Conversely, unemployed individuals getting a job opportunity always return to employment provided they do not get a better entrepreneurial opportunity.

Their recursive program is:

$$
\begin{aligned}
W(\mathbf{x}_w, J) = \max_{c,a',s_e} u(c,0,s_e) + \beta\mathbb{E}\Big\{(1-\eta)\Big[W(\mathbf{x}'_w, J) + \pi_e(s_e)\max\left\{E(\mathbf{x}'_e,0) - W(\mathbf{x}'_w, J), 0\right\}\Big] \quad (3)\\
+\eta\Big[(1-q)\left[U(\mathbf{x}'_u, J) + \pi_e(s_e)\max\left\{E(\mathbf{x}'_e,0) - U(\mathbf{x}'_u, J), 0\right\}\right]\\
+q\left[U(\mathbf{x}'_u, 0) + \pi_e(s_e)\max\left\{E(\mathbf{x}'_e,0) - U(\mathbf{x}'_u, 0), 0\right\}\right]\Big]\Big| y, \vartheta\Big\},
\end{aligned}
$$

$$\text{s.t.} \quad c + a' = (1-\tau_w)h(\vartheta)wy + (1+r)a, \tag{4}$$

$$c > 0,\ a' \geq 0,\ s_e \geq 0, \tag{5}$$

where τ_w is a flat labor income tax and equation (4) is the budget constraint of the worker.

2.1.2 Unemployed individual

We specify the UI program to capture key features of the UI system in the US while maintaining the tractability of the model. The exact number of remaining periods with UI benefits is an important component which is tracked by the state variable $j \in \{0, ..., J\} \equiv \mathcal{J}$. We note $\{b(\vartheta, j)\}_{j=J}^{j=0}$ the path of UI benefits. Consistent with what is implemented in the US, the amount of benefits of an eligible unemployed individual, $b(\vartheta, j)$, is related to her past earnings through $h(\vartheta)w$, up to a replacement rate μ and subject to a cap defined by the maximum benefit amount $\overline{b}$. $\overline{J}$ is the exogenous regulatory maximum UI duration converted to model periods but, due to discretization, this number can fall between two model periods. To implement the exact number of regulatory UI benefits periods, we set J as the number of model periods immediately above $\overline{J}$ and then apply a linear rule to provide only partial UI benefits in the last model period before losing coverage. UI benefits in the current period are:

$$
b(\vartheta, j) = \begin{cases} \widetilde{b}(\vartheta)(1-\tau_w) & \text{if } j \in [2, J] \\ \widetilde{b}(\vartheta)(1-\tau_w)\Big[1-(J-\overline{J})\Big] & \text{if } j = 1 \\ 0 & \text{if } j = 0 \end{cases}, \quad \widetilde{b}(\vartheta) = \begin{cases} w\mu h(\vartheta) & \text{if } w\mu h(\vartheta) \leq \overline{b} \\ \overline{b} & \text{otherwise} \end{cases}, \tag{6}
$$

With the above rule, agents can be either insured ($j > 0$) or uninsured ($j = 0$). Consistent with the current US unemployment insurance scheme, laid-off workers are eligible for UI and are assumed to have maximum insurance duration (i.e. $j = J$) while non-laid-off workers and entrepreneurs are uninsured (i.e. $j = 0$).

Following the above scheme, insured unemployed individuals ($j > 0$) receive benefits $b(\vartheta, j)$, in proportion to their individual productivity ϑ. By claiming UI in the current period, they shift from j periods of remaining UI rights to $j-1$ at the end of the period. However, this shift is only allowed if individuals actively searched for a job and provided enough effort to meet the applicable UI regulations.[8] $\pi^m(s_w)$ is the probability to meet this requirement. This can be viewed as stylized imperfect monitoring of program applicants due to, for instance, asymmetric information. Non eligible individuals and those who have exhausted their rights ($j = 0$) receive no benefits. Moreover, all unemployed individuals are assumed to receive a fixed amount m from domestic production. Unemployed individuals search for both a business idea and a job opportunity with respective efforts s_e and s_w and corresponding success probabilities $\pi_e(s_e)$ and $\pi_w(s_w)$. Upon finding a job, they become workers with continuation value $W(\mathbf{x}'_w, J)$. Similarly, upon having an idea, a business can be started in the next period with continuation value $E(\mathbf{x}'_e, 0)$. Their recursive program is:

$$
\begin{aligned}
U(\mathbf{x}_u, j) = \max_{c,a',s_e,s_w} \; & u(c, s_w, s_e) + \beta \mathbb{E}\Big\{ \pi_w(s_w) \Big[W(\mathbf{x}'_w, J) + \pi_e(s_e) \max\{E(\mathbf{x}'_e, 0) - W(\mathbf{x}'_w, J), 0\} \Big] \\
& + (1 - \pi_w(s_w)) \Big[\pi^m(s_w) U(\mathbf{x}'_u, j-1) + (1 - \pi^m(s_w)) U(\mathbf{x}'_u, 0) \\
& \qquad + \pi^m(s_w) \pi_e(s_e) \max\{E(\mathbf{x}'_e, 0) - U(\mathbf{x}'_u, j-1), 0\} \\
& \qquad + (1 - \pi^m(s_w)) \pi_e(s_e) \max\{E(\mathbf{x}'_e, 0) - U(\mathbf{x}'_u, 0), 0\} \Big] \Big| \, \vartheta \Big\},
\end{aligned}
$$

$$
\text{s.t.} \quad c + a' = m + b(\vartheta, j) + (1 + r)a, \tag{7}
$$

$$
c > 0, \; a' \geq 0, \; s_e \geq 0, \; s_w \geq 0, \; \textit{Equation } (6), \tag{8}
$$

where equation (7) is the corresponding budget constraint.

2.1.3 Entrepreneurs

Entrepreneurs produce using capital k and their own labor $\underline{l}$ in their self-employed business using technology:

$$
\mathcal{Y}(k, \vartheta, z) = z g(\vartheta) \left[\varpi k^p + (1 - \varpi) \underline{l}^p \right]^{\nu / p} \tag{9}
$$

with $\nu \in (0, 1)$ the degree of homogeneity which characterizes returns to scale, $p > 0$ the degree of substitutability, and $\varpi \in [0, 1]$ the share of each production factor. Equation (9) departs from the standard specification in models with entrepreneurs found in Quadrini (2000), Cagetti and De Nardi (2006), or Kitao (2008) among others. This specification lets us generate self-employment income even without any business capital k. This assumption is empirically relevant given our broad definition of entrepreneurship: in the Survey of Consumer Finances (SCF), about 35-40% of the self-employed individuals are using less than 1000$ of business capital. In Section 3, we show that this specification also lets us better capture the gross flows

[8] Despite specific local UI regulations, in most states, monitoring relies on the weekly obligation to report any job search activities to the U.S. Department of Labor (Asenjo et al., 2019).

in and out of entrepreneurship estimated from the SIPP. The function $g : \vartheta \mapsto \mathbb{R}$ maps individual ability into entrepreneurial ability. However, due to the presence of the entrepreneurial business shock z and the transitory match-quality shock y, there is an imperfect correlation between labor and entrepreneurial incomes.

To invest k, entrepreneurs can borrow from a financial intermediary funds that can only be invested in the business. Recalling that a is the current wealth of an agent, entrepreneurs choose whether to borrow ($k > a$) or save ($k < a$). If they borrow the amount $(k - a)$, we assume that it is only up to a fixed fraction λ of their total assets. This type of borrowing constraint has been widely used in the context of entrepreneurship (see Kitao (2008); Brüggemann (Forthcoming) among many others). Entrepreneurial profit $\mathcal{P}$ is defined as entrepreneurial production net of capital depreciation, any interest repayment, and the fixed cost c_f. The latter accounts for all the additional functioning costs that entrepreneurs face. By providing effort s_w, entrepreneurs can search for a job opportunity *on-the-business* and change occupation in the next period with probability $\pi_w(s_w)$ and value $W(\mathbf{x}'_w, J)$. Otherwise, if they endogenously choose to quit entrepreneurship, they can return to the uninsured unemployment pool with value $U(\mathbf{x}'_u, 0)$. Finally, an entrepreneur faces an exogenous probability to fall in an absorbing state $z_0 = 0$ with probability p_{z_0} which translates the fact that some entrepreneurs might fail independently of their ability to self-insure against bad business shocks.[9] In such a case, she will exit to either employment or unemployment depending on her job search effort. The recursive program of entrepreneurs is:

$$\begin{aligned} E(\mathbf{x}_e, 0) = \max_{c,a',k,s_w} u(c, s_w, 0) + \beta \mathbb{E}\Big\{ & \pi_w(s_w) \max\{W(\mathbf{x}'_w, J), E(\mathbf{x}'_e, 0)\} \\ & + (1 - \pi_w(s_w)) \max\{U(\mathbf{x}'_u, 0), E(\mathbf{x}'_e, 0)\} \Big| z, \vartheta \Big\}, \end{aligned} \tag{10}$$

$$\text{s.t.} \quad c + a' = (1 - \tau_p)\mathcal{P}(k, \vartheta, z) + a + r(a - k)\mathbb{1}_{\{k \le a\}}, \tag{11}$$

$$\mathcal{P}(k, \vartheta, z) = \mathcal{Y}(k, \vartheta, z) - \delta k - r(k - a)\mathbb{1}_{\{k \ge a\}} - c_f, \tag{12}$$

$$k \le \lambda a, \tag{13}$$

$$c > 0, a' \ge 0, s_w \ge 0. \tag{14}$$

with δ the depreciation rate, equation (11) is the budget constraint, and equation (13) is the borrowing constraint.[10] τ_p is a payroll tax rate. Finally, notice that although entrepreneurs do

[9] For the sake of clarity, we augment the Markov process z with an additional state $z_0 = 0$ and redefine the transition matrix with $\widetilde{\pi}_z(z'|z) = \pi_z(z'|z)(1 - p_{z_0})$ for $z, z' \in \{z_1, ..., z_Z\}$, $\widetilde{\pi}_z(z_0|z \in \{z_1, ..., z_Z\}) = p_{z_0}$ and $\widetilde{\pi}_z(z' \in \{z_1, ..., z_Z\}|z_0) = 0$, $\widetilde{\pi}_z(z_0|z_0) = 1$, with $\pi_z(z'|z)$ the discretized transition matrix of the above AR(1) process.

[10] Recall that the cash on hand of entrepreneurs in the baseline case can be written: $\mathcal{Y}(k, \vartheta, z) + (1 - \delta)k - (1 + r))(k - a)\mathbb{1}_{\{k \ge a\}} + (1 + r)(a - k)\mathbb{1}_{\{k \le a\}}$. Rearranging terms yield profit and budget constraint equations.

not benefit from the UI program, they can always self-insure using their wealth.

2.2 Corporate sector

A representative corporate firm produces Y_t using a Cobb-Douglas technology, with total factor productivity A, capital level K_t and labor L_t, such that: $Y_t = F(K_t, L_t) = AK_t^{\alpha} L_t^{1-\alpha}$, where $\alpha \in (0,1)$ is the capital share.[11] Profit maximization produces the competitive interest rate $r_t = A\alpha \left(\frac{L_t}{K_t}\right)^{1-\alpha} - \delta$ and wage rate $w_t = A(1-\alpha)\left(\frac{K_t}{L_t}\right)^{\alpha}$.

2.3 Government

The government runs an UI system that covers the pool of recently laid-off unemployed individuals and finances it using labor income and payroll taxes. In our benchmark economy, in order to not distort occupational choices in counterfactuals experiments, we assume that UI is equally financed by a symmetric tax scheme on entrepreneurs and workers, such that $\tau = \tau_w = \tau_p$. The validity and consequences of this assumption are discussed in Appendix A.2. Total government revenues (T) are:

$$T = \int_j \int_{\mathbf{x}_w} \tau_w h(\vartheta) wy \, d\Gamma(\mathbf{x}_w, j) + \int_{\mathbf{x}_u} \tau_w b(\vartheta, j) \, d\Gamma(\mathbf{x}_u, j) + \int_{\mathbf{x}_e} \tau_p \mathcal{P}(k, \vartheta, z) \, d\Gamma(\mathbf{x}_e, j), \tag{15}$$

with $\Gamma(\mathbf{x}_o, j)$ the measure of individuals in occupation o with remaining UI duration j. Total government expenditures G are equal to the allocated UI benefits: $G = \int_j \int_{\mathbf{x}_u} b(\vartheta, j) \, d\Gamma(\mathbf{x}_u, j)$.

2.4 Equilibrium

A stationary recursive equilibrium in this economy consists of a set of value functions $W(\mathbf{x}_w, j)$, $U(\mathbf{x}_u, j)$, $E(\mathbf{x}_e, j)$, policy rules over asset holdings $a'(\mathbf{x}_o, j)$, consumption $c(\mathbf{x}_o, j)$, job search effort $s_w(\mathbf{x}_o, j)$, business search effort $s_e(\mathbf{x}_o, j)$, business investment $k(\mathbf{x}_e, j)$, occupational choices, prices $(r, w) \in \mathbb{R}^+$, tax rate $\tau \in \mathbb{R}^+$ and a stationary measure over individuals $\Gamma(\mathbf{x}_o, j) \, \forall o, j$, such that: (i) Given prices (r, w) and tax rate τ, the policy rules and value functions solve household individual programs; (ii) The wage w and the interest rate r are equal to the marginal products of the respective production factor in the corporate sector; (iii) goods and factor markets clear: (a) capital: $\int a'(\mathbf{x}_o, j) d\Gamma(\mathbf{x}_o, j) = K + K^E$, with aggregate entrepreneurial capital

[11] Unlike Cagetti and De Nardi (2009), we abstract from entrepreneurial labor demand. However, we believe our setup is sufficient to replicate the dynamics of the data. Indeed, with a static entrepreneurial labor demand, workers are hired in proportion to entrepreneurial capital and productivity and the wage rate. Mechanically, a higher number of entrepreneurs lead to a higher labor demand and thus a higher equilibrium wage. In our setting, as the number of entrepreneurs reduces the labor force in the corporate sector, its labor supply is lower, and therefore equilibrium wages increase.

$K^E = \int k(\mathbf{x}_e, j)d\Gamma(\mathbf{x}_e, j)$, (b) the measure of corporate workers $\int d\Gamma(\mathbf{x}_w, j)$ is equal to corporate labor demand; (iv) $\Gamma(\mathbf{x}_o, j)$ is the stationary measure of individuals induced by the decision rules and the exogenous Markov processes; (v) τ balances the government budget ($T = G$). Finally, we define total output $\mathbb{Y}$ as the sum of corporate sector output Y and entrepreneurial sector output Y^E such that $\mathbb{Y} = Y + Y^E = Y + \int_{\mathbf{x}_e} \mathcal{Y}(k(\mathbf{x}_e), \vartheta, z)d\Gamma(\mathbf{x}_e, j)$.

This model has no analytical solution and must be solved numerically. We detail our numerical implementation of this problem in Online Appendix 3.

2.5 Taking the Model to the Data

We parameterize the model to fit key features of the US gross labor market flows between employment, unemployment, and entrepreneurship as well as key feature related to the entrepreneurial sector. Our data counterparts are taken from the CPS, 1994:IV-2015-IV, the 2004 Survey of Consumer Finances (SCF), and the SIPP, 1996:2013.

Prior to the calibration exercise and to be consistent across the different surveys, we start by defining the comparable groups of individuals in the data. We separate individuals into three groups: employed (W), unemployed (U), and entrepreneurs seen as all self-employed agents (E). While some papers use a narrower definition of entrepreneurship based on business ownership with an active management role (see Cagetti and De Nardi (2006) or Brüggemann (Forthcoming)), this approach ignores an important fraction of self-employment and its contribution to the gross labor market flows. Moreover, this notion of entrepreneurship is relevant in the specific framework where entrepreneurs can not produce without physical capital. In contrast, our model explicitly accounts for entrepreneurs who run activities with very little physical capital and use mostly their own labor instead.

2.5.1 Labor Market Mobility and Entrepreneurship: stylized facts

Most of our occupational transitions are derived using the CPS data for the 1994:IV-2015-IV period. We consider all respondents between the ages of 20 and 65 and do not restrict to household heads. 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. Importantly, our procedure to establish the flows also corrects for high-frequency reversals of transitions between entrepreneurship and unemployment. For instance, based on this procedure, U – – E – U transitions (from unemployment to entrepreneurship and back over the quarter) are recoded as U – – – U. We perform similar adjustments for U – –

U – E cases. As such, only U – – E – E transitions are coded as U – – – E. This restriction helps in reducing mismeasurements due to possible misreporting (see Farber et al. (2015) and Krusell et al. (2017)). All our results are qualitatively robust without this restriction. We classify as a worker an individual currently working in a paid job or declaring being temporarily absent from a paid job. We classify unemployed individuals as those who did not have a job while being in the labor force. Unemployed agents eligible for UI are job losers/on layoff and other job losers. We further condition the *layoff* category with unemployment duration that can not exceed the UI duration. Entrepreneurs are active self-employed individuals.[12] We use the longitudinal weights provided by the CPS. Further details regarding data construction are available in the Online Appendix.

Table. 1. Aggregate quarterly occupational gross flows rates.

	Gross flow (%) to			**Masses** (%)
From	*Employment*	*Entrepreneurship*	*Unemployment*	
Employment	97.32	0.70	1.97	84.3
	(0.45)	(0.11)	(0.43)	
Entrepreneurship	6.30	92.26	1.45	10.3
	(1.28)	(1.49)	(0.64)	
Unemployment	44.38	3.56	52.06	5.4
	(10.24)	(1.19)	(10.47)	

Source: authors' computations using CPS data from 1994:IV-2015-IV. We restrict our sample to individuals between the ages 20 and 65. Gross flows are corrected for misreporting. Standard deviations between brackets.

In Table 1, we characterize the resulting aggregate gross flows between occupations and the associated occupational masses. While the existing literature has documented the flows in and out of employment and unemployment, we focus on the decomposition of the transitions in and out of entrepreneurship. We discuss two key facts that a model of the three labor market statuses should account for. First, employment is a significantly more persistent occupation than entrepreneurship. Self-employed individuals have an average quarterly exit rate of 7.75% (with 1.45% toward unemployment) compared to 2.67% for employed individuals. A possible explanation is related to the risk faced by entrepreneurs (Herranz et al., 2015). Additionally, the flows out of the above two activities have differing characteristics: most of the flows out of employment are toward unemployment whereas most of those out of entrepreneurship are toward employment. Therefore, many entrepreneurs voluntarily cease their businesses for a job while not experiencing any unemployment period. Second, unemployed individuals are

[12] A robustness check adds the fact that self-employed agents own their business using the variable HHBUS = 1, which is available only after 1994. 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 self-employed/entrepreneurs is close to the one estimated using the SCF (8-9%), we believe that our estimate is consistent.

about 5 times more likely to enter entrepreneurship than workers: 3.6% of the unemployed individuals and 0.7% of the workers start a business each quarter. We stress at least two explanations: (i) workers spend less time searching for business ideas and learning about potential business markets, and (ii) unemployed individuals may choose to enter entrepreneurship as a better outside opportunity or out-of-necessity. Our model will account for both margins. As a result, while representing only 5-6% of the workforce, unemployed individuals account for 20% of the individuals transiting into entrepreneurship.

2.5.2 Exogenously calibrated parameters

We now describe our calibration strategy. Some parameters are assigned using standard values or estimates in the literature in this section while others are endogenously chosen to reproduce key moments observed in the data in the next section. A model period is set to two months.[13]

Parameters related to the production sectors are set as follows. We normalize TFP to unity at yearly frequency, implying that $A = 1/6$ given the periodicity of the model. We set the depreciation rate δ to a standard value of 6.1% annually or 1% every two months. The capital share in the corporate sector α is set to 0.33. As in Kitao (2008), we set the borrowing parameter λ to 1.5. The entrepreneurial labor supply $\underline{l}$ is normalized to 1. In the absence of an empirical counterpart, we set $p = 1.0$ (perfect substitutability between entrepreneurial capital and its own labor) in the baseline case and also study the Cobb-Douglas case ($p \to 0$). Consistent with estimates in Castro et al. (2015) and values used in Clementi and Palazzo (2016), the idiosyncratic business process z has a standard deviation $\sigma_z = 0.22$ and persistence $\rho_z = 0.91$, which corresponds to an annual persistence of 0.57. Moreover, the exogenous exit probability of entrepreneurs is set to 20% of the total entrepreneurial exit probability (5.8% each period), yielding $p_{z0} = 0.0116$.[14] This is in the range of the 20-30% of long-established business owners declaring ceasing their activity due to reasons not related to economic conditions in the Survey of Business Owners (2007) and the Annual Survey of Entrepreneurs (2014:2016).

We normalize the persistent individual working ability $h(\vartheta)$ to ϑ and set the persistence ρ_ϑ to 0.985 corresponding to an annual persistence of about 0.91. The standard deviation σ_ϑ is set to 0.21 in order to generate an earnings Gini coefficient of 0.38. For the transitory match-quality process y, ρ_y is set to 0.85, corresponding to an annual persistence of 0.38, and σ_y to 0.175.

[13]We produce robustness checks for a lower and a higher frequency of the model periodicity. Results are qualitatively similar. The current periodicity was chosen because transition flows in and out of entrepreneurship in the data have more observations as compared to a monthly (or lower) frequency.

[14]The bimonthly flows used to pin down these numbers are in Table 3 while the quarterly flows are in Table 1.

We set the coefficient of relative risk aversion $\sigma = 1.25$. The home production parameter m is set to 0.025, which corresponds to 11% of the average wage in the economy consistent with the fact that only 11% of total consumption spending could be replaced with home-production according to Been et al. (2020). In the benchmark case, the search elasticities ψ and ϕ are both set to 2.0 to generate separable quadratic search costs. [15]

Regarding the gross flows relative to unemployment, we use a linear relation of the $W \to U$ transition characterized by the separation rate $\eta(\vartheta)$ with respect to earnings in the CPS. We specify: $\eta(\vartheta) = \alpha_\eta + \beta_\eta wh(\vartheta)$, where α_η and β_η are estimated using earning quantiles as a proxy for $wh(\vartheta)$. We obtain $\alpha_\eta = 0.0252$ and $\beta_\eta = -0.0047$. Moreover, to better account for CPS transition flows, each period, a fraction $\zeta = 0.8\%$ of individuals retires and is replaced by young uninsured unemployed individuals that enter the workforce with zero net worth and ability ϑ drawn from the invariant distribution Π_ϑ.

The benchmark UI replacement rate μ is set to 0.45, close to the US across states average replacement rate in the last decades, and the UI duration is set to $\overline{J} = 3$, which corresponds to 26 weeks of regular benefits. The UI cap $\overline{b}$ is set to represent 50% of the average wage, which corresponds approximately to the average applied across US states.

2.5.3 Endogenously calibrated parameters and target moments

We now describe parameters picked endogenously to match targets in the data. Although a given parameter does not affect only one particular moment due to the nonlinearity of the model, specific parameters can be somewhat tied to particular moments.

The respective probabilities of getting a business idea, a job opportunity, or meeting the active job search requirement arrive at a Poisson rate such that:

$$\pi_e(s_e) = 1 - e^{-\kappa_e s_e}, \qquad \pi_w(s_w) = 1 - e^{-\kappa_w s_w}, \qquad \pi_m(s_w) = 1 - e^{-\kappa_m s_w},$$

with κ_e and κ_w matching parameters and κ_m the elasticity of monitoring. κ_w is set to capture the 40.1% of unemployed individuals transiting toward employment as observed in the CPS and κ_e is set to match the fraction of entrepreneurs in the economy. The literature uses various definitions of entrepreneurship. We consider self-employment in the broader sense as it is the relevant measure for our analysis.[16] In the CPS and the SCF, the mass of self-employed

[15] In Appendix A.2, we allow for non-separable search intensities, i.e. $\phi \neq \psi$. Our results are qualitatively similar.

[16] In an alternative setting with entrepreneurs defined as active self-employed business owners (available upon request), most of our results were qualitatively similar.

individuals is about 10.5% and 12.5% respectively. Therefore, we target a self-employment rate of 12%. Finally, we choose κ_m such that 4% of the insured unemployed individuals are sanctioned following detection by the UI agency in equilibrium, consistent with estimates in Grubb (2001).

The estimation of $g(\vartheta)$ is challenging since the contribution of the skills of an entrepreneur to the performances of a business is generally unobservable. We indirectly infer the mapping between worker and entrepreneur individual productivity using the observed relationship in the $W \rightarrow E$ transition by earnings quantiles. We divide the labor income distribution into 3 quantiles and compute in each the ratio of workers starting a business over the average ratio of workers starting a business in the economy. Over our CPS sample period, workers in the first earnings quantile are 19-20% more likely to start a business than the average worker. In the middle quantile, they are about 14-15% less likely. In the third quantile, they are 2-3% more likely. We use those relative flows to pin down the following values: $g(\vartheta) = [0.136, 0.200, 0.289]$. The resulting transition flows relative to the average flow in the model implies that workers are 19% more likely to become entrepreneurs in the first earnings quantile, 15% less likely in the second quantile, and 1% more likely in the third quantile.

The remaining parameters are chosen as follows. The discount factor β helps to generate a realistic annual capital (excluding public capital) to output ratio of 2.6. Our model accounts for the fact that not all unemployed individuals are eligible for UI. We, therefore, set the exogenous probability for a worker to voluntarily quit her job, q, to replicate the observed insured unemployment rate (IUR) of 2.6. The returns to scale parameter in the entrepreneurial sector ν lets us fit the 23% of total income received by the entrepreneurs in the SCF. The fixed cost c_f captures the 5.8% of entrepreneurs who exit each period in the CPS. The share ϖ in the entrepreneurial production function is used to generate a gross flow of unemployment transiting to entrepreneurship in the second wealth quantile relative to the average flow from unemployment to entrepreneurship of 0.90. Table 2 reports these parameters and related targets.

Table. 2. Calibrated parameters and fit.

	Parameter	**Value**	**Moment**	**Target**	**Model**
Discount factor	β	0.986	K/Y (annual)	2.6	2.6
Returns to scale	ν	0.638	Entrepreneur's share of total income (%)	23.0	22.4
Monitoring	κ_m	3.770	Share of sanctioned eligible unemployed (%)	4.0	4.3
Fixed cost	c_f	0.081	Exit rate from entrepreneurship (%)	5.8	5.8
Unvoluntary exit	q	0.250	Insured unemployment rate (%)	2.6	2.6
Matching prob.	κ_e	0.274	Share of entrepreneurs (%)	12.0	12.0
Matching prob.	κ_w	0.639	$U \rightarrow W$ transition (%)	40.1	40.0
Entrep. ability	$g(\vartheta)$	*See text*	W to E by quantile/avg rate (%)	*See text*	*See text*
Entrep. capital share	ϖ	0.249	Flow $U \rightarrow E$ in $T2$ wealth relative to average	0.90	0.85

3 Gross Flows: Aggregate Characteristics and Micro Level Behaviors

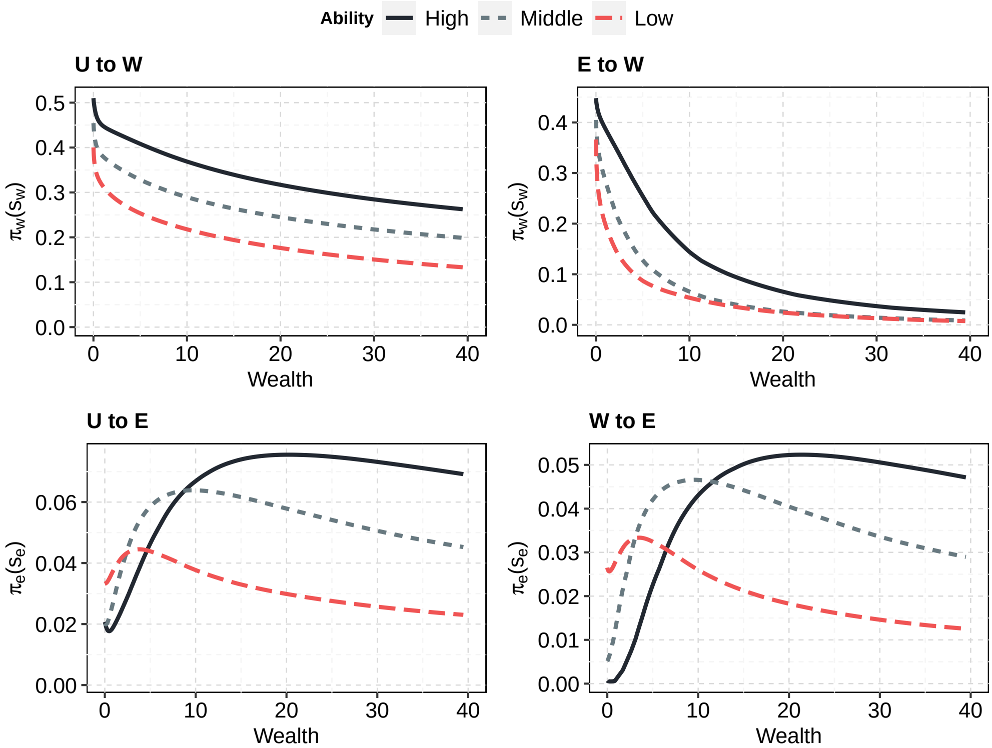
In this section, we assess the ability of our benchmark economy to generate key properties of the data on labor market flows. We first discuss the gross labor market flows along the wealth and the ability distributions and then verify our fit in a number of additional dimensions.

3.1 Optimal search efforts

With ability and wealth, the model embeds two parsimonious dimensions of heterogeneity that have an influence on occupational flows. Figure 1 (top panels) reports how those dimensions interact with optimal job and business search efforts. The model job search effort s_w is consistent with long-established results (see for example Lentz and Tranaes (2005) among others): the optimal job search effort is decreasing in wealth, for both unemployed individuals and entrepreneurs. Wealth provides a means to smooth consumption that conditions the ability to wait for a job and in turn the search effort. Moreover, wealthy individuals are able to establish bigger profitable firms that eliminate the incentive to search for a job. We also illustrate that the higher the ability, the higher the job search effort in the case of unemployed individuals. For high-ability individuals, there is a clear opportunity cost of unemployment with respect to the high wages they can earn in employment. There is a similar effect for relatively wealth-poor entrepreneurs looking for a job.

The more novel aspects here are displayed in the bottom panels: the optimal business search efforts s_e are hump-shaped with respect to wealth. This is due to two opposing effects. First, wealth-poor individuals, who are the most likely to be credit constrained, do not find it interesting to run very small firms and thus provide very small effort. This effect is mitigated, most notably for unemployed individuals, by the introduction of our CES entrepreneurial production function: the efforts to set up a business are positive at zero wealth for those individuals whereas no effort would have been provided in the standard Cobb-Douglas case. Then, as wealth increases, individuals can invest larger capital amounts in their businesses and increase their search effort. Second, beyond a certain wealth level, incentives to establish a business diminish. Similar to looking for a job opportunity, wealthy unemployed individuals face search disincentives due to their important financial wealth compared to the additional income business capital can procure. The same is true for employed individuals looking to create a business *on the job*. We also find that wealth-poor low-ability individuals search more than the corresponding high-ability individuals. For richer individuals, this ordering is reversed. Low-ability individuals have lower UI benefits which make it more advantageous for them to invest in a business earlier as their wealth increases. But they also have a low ability to run a business which makes them reach the above threshold faster. High-ability individuals receive higher UI benefits and go through the same phases but at higher levels of wealth. The same type of reasoning applies to workers searching *on the job* for a business opportunity but relative to their current wage instead of UI benefits. In the next section, we show that those policy functions generate consistent gross flows between occupations across ability levels and across the wealth distribution.

Figure 1. Implied optimal probability to find a job for unemployed individuals (top left) and entrepreneurs (top right). Implied optimal probability to find a business idea for unemployed individuals (bottom left) and workers (bottom right).



Note: the worker's match component y and the entrepreneur's business shock z are set to their average values. Policy functions out of unemployment are for $j = J$.

3.2 Resulting gross flows

Aggregate gross flows Our calibrated model successfully replicates a number of empirical characteristics of gross labor market flows in the US economy even outside explicitly targeted moments. Table 3 reports bimonthly aggregate gross flows between employment, unemployment, and entrepreneurship. The calibrated model is able to closely capture gross flows in the

CPS, including a number of them that are endogenously generated by the model.[17]

The model captures that unemployed individuals are more likely than workers to start a business, and replicates the high $E \to W$ transition (4.5%) and low $E \to U$ transition (1.4%). Using the 2014 CPS, the Kauffman Indicators of Entrepreneurship reports a share of new entrepreneurs out-of-unemployment of 20.5%, against 19.9% in the model. This fraction is higher for individuals with less than a high school degree (26.5%) and lower for college graduates (17.4%). In the model, the corresponding shares are consistent: 25.4% and 21.2% for low and high ability respectively. Beyond the required match of aggregate occupational flows, recent research has stressed the importance of consistent micro-level behaviors concerning gross flows (see for instance Krusell et al. (2017)). We now discuss the model ability to fit gross flows in two dimensions of interest – ability and wealth – which have been shown to play an important role in occupational decisions regarding entrepreneurship (see Quadrini (2000) or Cagetti and De Nardi (2006)) and for unemployed individuals (see Chetty (2008)).

Table. 3. Bimonthly gross flow between occupations in the data and the model.

	Data				Model			
	To			Masses	To			Masses
From	W	E	U		W	E	U	
W	97.83	0.50	1.67	84.3	97.40	0.78	1.82	82.4
	(97.78,97.88)	(0.49,0.51)	(1.63,1.72)					
E	4.53	94.16	1.31	10.3	4.48	94.15	1.37	12.0
	(4.51,4.56)	(94.01,94.30)	(1.25,1.38)					
U	40.10	3.40	56.51	5.4	40.15	2.81	57.04	5.6
	(38.94, 41.25)	(3.30,3.49)	(55.33,57.70)					

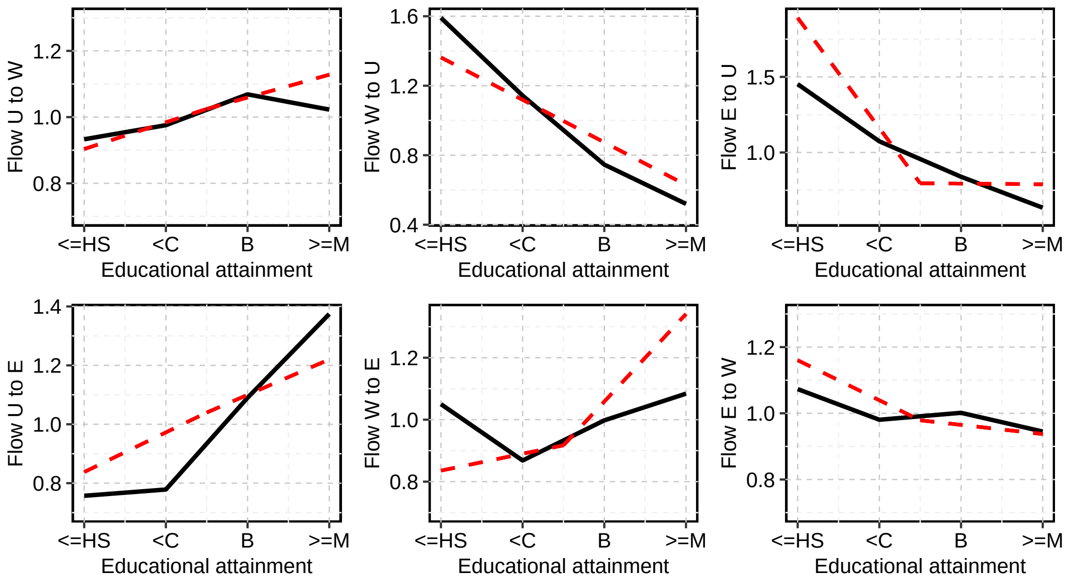
Data sources: authors' computations using CPS data from 1994:IV to 2015:IV. CPS Gross flows are corrected for misreporting. In parenthesis: the 95% confidence interval.

Gross flows by ability Figure 2 shows the flows by ability level in the model and in the data when we proxy for ability with educational attainment in the CPS. Our use of education is debatable. However, the CPS data do not provide any information concerning business earnings and unemployment compensation that might be relevant to validate the ability dimension. Education is, therefore, the best directly available variable comparable to the model. We divide educational attainment into four groups. $<= HS$: less than or equivalent to a high school degree; $< C$: some college but no degree; B: bachelor's degree; M: master's degree or higher (professional school and doctoral degrees). The above groups respectively account for 31.4%,

[17] Specifically, the $W \to U$ transition is captured by the $\eta(\vartheta)$ process. As we calibrated the model to match one occupational mass and two transitions, we are left with three degrees of freedom, since targeting masses also indirectly target some flows (up to the exogenous entry ζ). Remaining mismatches with respect to the data arise for instance due to transitions out of the labor force, death, or moves to other regions.

29.5%, 23.9%, and 15% of the workers 25 years and older according to the Bureau of Labor Statistics. Overall, the model is able to generate a good fit of the data with perhaps one caveat. Relative to its data counterpart, there is a low flow of workers to entrepreneurship for the lowest ability group. Aside from this, the model accounts exceedingly well for the flow patterns observed in the data. Notably, it fits well the slightly decreasing flow from entrepreneurship to employment, due to the higher risk faced by low-ability entrepreneurs relative to the fixed cost, which induces them to exit more often. Also, it fits the increasing flow of unemployment to entrepreneurship, most notably because high-ability workers are those with higher levels of wealth. This allows them to wait for the opportunity to run a business and to run a higher scaled more valuable business, conditional on the business shock z.

Figure 2. Gross labor market flows by ability level ϑ (model in dashed red) and educational attainment (CPS data in straight black).



Note: the data patterns are computed using quarterly flows to obtain a sufficient number of observations by educational attainment. Legend: $<= HS$, less than or equivalent to a high school degree; $< C$, some college but no degree; B, bachelor's degree, M, master's degree or higher (professional school and doctoral degrees).

Gross flows by wealth The decomposition of gross flows by wealth is a natural exercise to consider as wealth drives incentives to quickly exit unemployment due to borrowing constraints or to enter entrepreneurship as personal wealth scales the expected profits of a potential business. Because the CPS does not report individual wealth, we rely on the 1996-2008 (covering the December 1995 to November 2013 period with gaps) panels of the Survey of Income and Program Participation (SIPP). The range of these panels is two to four years. Households are interviewed three times a year about the previous four months in each panel and report their asset holdings two to four times within a panel at a yearly frequency. Those assets consist of savings and checking accounts, mutual funds, retirement accounts, real estate, business assets, and other equity. We use total wealth as a measure of individual wealth but our results are robust to choosing only liquid wealth (checking accounts and savings) as a proxy for wealth. Although the definitions of occupations in the SIPP and the CPS slightly differ, we create close enough counterparts based on our explanations in Section 2.5.1.[18]

In the left panel of Table 4, we report the gross flow rates by wealth quantiles in the SIPP. The right panel reports the gross flow rates by wealth quantiles in the benchmark model and for an alternative case with a Cobb-Douglas entrepreneurial production function ($p \to 0$).

Table. 4. Occupational flow rates by wealth quantiles in the SIPP and the model.

	Data			Model					
				Benchmark			Case with $p \to 0$		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
$W \to E$	0.64	0.86	1.50	0.36	0.61	2.03	0.00	0.29	2.71
$W \to U$	1.52	0.85	0.63	1.18	0.98	0.84	1.21	0.98	0.82
$E \to W$	1.17	1.03	0.80	1.56	0.96	0.48	2.49	0.31	0.21
$E \to U$	1.87	0.78	0.34	1.59	0.85	0.56	2.28	0.53	0.19
$U \to E$	0.70	0.96	1.34	0.65	0.85	1.50	0.00	0.59	2.41
$U \to W$	0.96	1.01	1.04	1.25	0.97	0.77	1.27	1.03	0.70

Data sources: authors' computations using the SIPP (1996-2008) panels. The alternative model with a Cobb-Douglas entrepreneurial production function ($p \to 0$) is calibrated to match the K/Y ratio and the masses of occupations.

Overall, the benchmark economy does a qualitatively and quantitatively reasonable job at matching the gross flows by wealth quantiles in the SIPP data. Starting with the flows out of employment, we find that the W to E transition is increasing in wealth. In the model, this is due to the fact that the value of entrepreneurship is higher when a bigger level of business capital is achievable. In that case, conditional on having the opportunity, wealthy individuals find it more valuable to run their own businesses instead of remaining workers. The W to U transition is decreasing. This is due to the selection of high-ability types with lower firing rates at higher levels of wealth. The E to W and E to U transitions are decreasing both in the data and the model. Intuitively, the wealthy can self-insure against the risk of an adverse business shock using their own wealth and are thus less likely to exit. This is also a result of the effect of wealth on the incentive to exit entrepreneurship because businesses are scaled to personal wealth due to the collateral constraint, as illustrated in Figure 1. The U to E transition is increasing, consistent with the mechanism described for the W to E transition. Finally, the U to W transition is nearly flat in the data but decreasing in the model. This discrepancy can be

[18]In the Online Appendix 1.3.2, we show the aggregate transition matrix between occupations in the SIPP. The latter is quite similar to the CPS analog above. However, as discussed in Krusell et al. (2017), there are a number of differences between flow rates in the SIPP and the CPS.

explained by the fact that, in the model, wealth-poor individuals have a higher incentive to search for a job opportunity.[19] This is related to the fact that the job-finding rate is parsimoniously modeled using the single parameter κ_w. In reality, low-ability individuals self-select at the bottom of the wealth distribution and are less likely to find a job.

As illustrated by the case $p \to 0$ in Table 4, it is worth noting that a model where entrepreneurs are precluded from producing by using only their own labor significantly changes the flows in and out of this occupation. In such an environment, individuals in the first wealth quantile are unwilling to become entrepreneurs, which is at odds with the SIPP evidence. This still is due to the fact that production is scaled to the business capital (and, in turn, to personal wealth). By letting entrepreneurs produce only with their own labor, the benchmark model somewhat disconnects the link between wealth and the propensity to start a business.[20]

3.3 Additional validation

Our model captures other moments related to the labor market and entrepreneurship that are not explicitly targeted but that are still reasonably well matched. As argued by Hamilton (2000) and Astebro and Chen (2014), some entrepreneurs create and keep running a business although they would earn more as workers. The share of *out-of-necessity* entrepreneurs, defined as entrepreneurs who started businesses because of a lack of job opportunities, i.e. because $\mathbb{E}_y[W(\mathbf{x})] > E(\mathbf{x}) > U(\mathbf{x})$, is equal to 7.7% in our model and is evaluated by Ali et al. (2008) to be 4.7% of early-stage entrepreneurs for men and 21.4% for women, representing 10% in total. In the pool of previously unemployed new entrepreneurs in the model, in line with Caliendo and Kritikos (2009), this represents a fraction of about 39% *out-of-necessity* entrepreneurs.

The model also has cross-sectional implications regarding the income and wealth distributions. The median ratio of entrepreneurial (resp. worker's) income (including capital gains) to net worth (i.e. total assets minus debt) is 0.19.5 (resp. 0.88) in the model, while it is 0.19 (resp. 0.73) in the data. In the model, the median ratio of entrepreneurial income over workers' income is 1.7 against 1.4 in the SCF. Entrepreneurs in the model own roughly 29% of total capital, in line with the 33% found by Cagetti and De Nardi (2006). In terms of wealth distribution, the median ratio of the net worth between entrepreneurs and the whole population is 6.4 in the

[19] Krusell et al. (2017) also report a similar discrepancy for the same reasons.

[20] We explored various mechanisms to generate such a behavior. First, we allowed for the possibility to partially rent capital, by rewriting the borrowing constraint as $k \leq \lambda a + \underline{h}$ with $\underline{h}$ a minimum amount of rentable capital. Second, we assumed two groups of individuals, including one with high non-pecuniary benefits of being an entrepreneur, independently of wealth. In those models, the resulting flows are harder to reconcile with the data.

model against 5.0-6.5 in the SCF. The fraction of zero (or negative) net worth is roughly 8% in the SCF, whereas it is 6% in our model. The model underestimates the wealth Gini: we find 0.67 compared to 0.8 in the SCF.[21] Overall, despite the few limitations that we underlined, to the best of our knowledge, our framework is the first to produce a close fit of the key features of gross labor market flows with entrepreneurship, both at the aggregate and micro levels.

4 Gross Flows: Responsiveness to UI generosity

This section studies the responsiveness of gross labor market flows to a change in labor market policy focusing on the case of UI variations. We begin by estimating the sensitivity of gross flows out of unemployment in the data and then examine the quantitative responsiveness in our calibrated model and describe the underlying drivers and long run adjustments.

4.1 Responsiveness to UI Generosity: Data

We exploit the heterogeneity in the UI system across US states and over time to study the interaction between UI generosity and occupational choice out-of-unemployment.[22] We use our CPS panel over the 1994:IV-2014:IV period and distinguish recently laid-off unemployed individuals who are eligible for UI from those who either voluntarily quit their job or are not eligible for UI. Our underlying assumption is that variations in UI generosity should mostly affect the eligible group. We use quarterly frequency to obtain sufficient flows toward self-employment and use the correction detailed in Section 2.5.1 to account for misreporting.[23]

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 (EB and EUC) comes from Farber et al. (2015). From 1994 to 2015, variations in the generosity of regular benefits are quite large, not only in the cross-section but also over time within states. Each state applies its own benefit schedule with a typical replacement rate of 35-50% of the previous wage of an individual with the level of benefits capped at each state's inflation-adjusted maximum weekly benefit level. Moreover,

[21] Regarding the wealth distribution, a version including a *superstar* state of business shock z is able to match the wealth distribution but produces similar results otherwise.

[22] Rothstein (2011) and Farber et al. (2015) study the effect of UI extensions on unemployment exit options. They focus on the timing of the switch toward employment and the potential disincentive effect. We focus on the effect of UI on the resulting occupational choices.

[23] The exact construction of the groups are provided in Section 2.5.1. We use benefit *eligibility* rather than benefit *receipt* as the latter is not available in the CPS. This is however not specific to this paper. Even in data with information on benefit receipts, Hsu et al. (2018) argue that self-reported information on UI payments is 30 to 40 percent lower than what administrative records show, and suggest *eligibility* as a proxy for actual UI receipts.

each state applies a limit on the number of weeks UI benefits can be claimed. A maximum of 26 weeks has been the typical UI duration, and variations in regular UI benefits are mostly driven by changes in the maximum weekly benefit amount (WBA). Following Agrawal and Matsa (2013) and Hsu et al. (2018), we define the generosity of regular UI benefits in state s as:[24] $Max\ Regular\ UI_{st} = Max\ WBA_{st} \times Max\ Regular\ Weeks_{st}$.

In recession periods, each state also provides extended benefits to individuals exhausting their regular benefits in the form of additional weeks. The Extended Benefits (EB) and the Emergency Unemployment Compensation (the successive names of this program having been EUC91, TEUC, and EUC08, we hereafter refer to it as simply EUC) are such regulations. During the Great Recession, heterogeneous emergency extensions (EB and EUC) of UI generosity were activated and in some states, the duration of UI benefits was extended up to 99 weeks. To represent the total UI generosity including the extensions, we define: $Max\ Extended\ UI_{st} = Max\ Regular\ UI_{st} + Max\ WBA_{st} \times Max\ EB\ EUC\ Weeks_{st}$,

This is the total amount of benefits that an individual falling into unemployment in a given month could claim over the maximum number of weeks benefits could be claimed at that time, including additional variations from the activation of UI extensions.

We distinguish three data panels in which the source of variations in UI generosity differs. Panel A covers the whole sample period from 1994 to 2015. Panel B covers the 1994-2007 period and excludes the Great Recession and the significant UI benefits extensions that were then implemented. It will let us study mostly the effects of a change in regular benefits. Panel C, covering the 2008-2015 period, encompasses the impact of all benefits changes including UI extensions. It will let us verify whether UI duration adjustments observed during the Great Recession result in similar findings with respect to regular benefits. Accordingly, for a laid-off unemployed individual eligible for UI benefits, we impose that the unemployment duration does not exceed 30 weeks in Panel B and 99 weeks in Panel A/C. This corresponds to the maximum UI duration, including extensions, in the respective Panels.

4.1.1 UI generosity and aggregate propensity to start a business

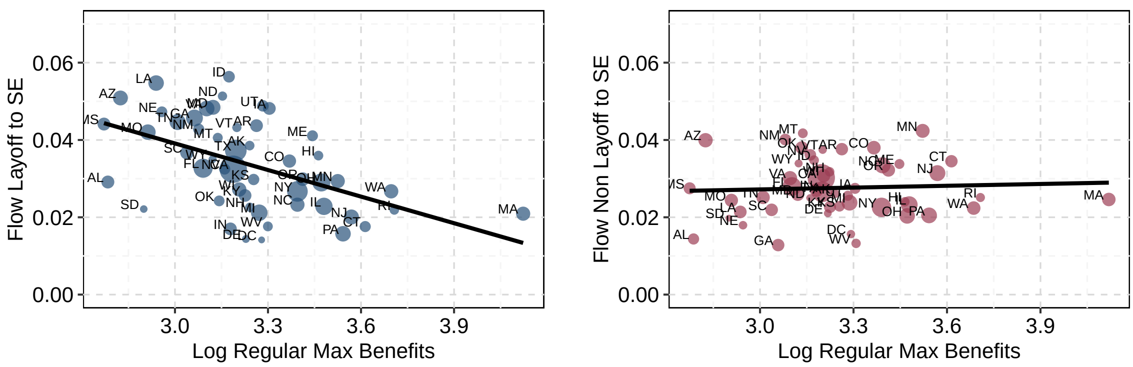
Recent papers, such as Røed and Skogstrøm (2014) and Hombert et al. (2020), show an important interaction between selection into self-employment and UI generosity. To establish

[24] Regarding the relation to actual UI benefits, Hsu et al. (2018) show that the elasticity of *Max Regular UI* to total actual compensation payments at the state level is 1.0. Furthermore, they show that for 60% of the population, benefits are capped, and that *Max WBA* captures changes in UI benefits well. To complement the analysis, we check the robustness of the results against alternative UI generosity measures in Appendix A.1.

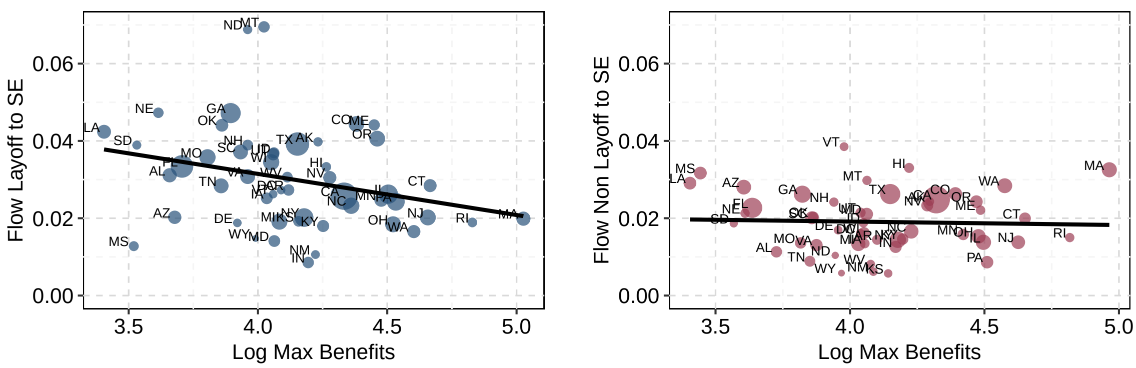
whether a relationship exists between UI generosity and flows to entrepreneurship in the US, we first show in Figure 3a the flows from unemployment to self-employment disaggregated by US states for Panel B. The left plot displays a downward relation between the maximum regular benefits level and flows from the pool of laid-off unemployed individuals to entrepreneurship. Namely, US states that have a higher maximum regular benefits level tend to have a smaller flow from the laid-off unemployment pool to self-employment. The right plot illustrates that such a downward relation does not exist for individuals that are unemployed for reasons other than a layoff and not eligible for UI. The left plot of Figure 3b establishes the same relation for Panel C, i.e. a timeframe where most of the UI benefits extensions offered after the Great Recession had come into implementation. Accordingly, when taking into account regular benefits as well as EB and EUC extensions, a higher generosity of UI is related to lower flows from the layoff pool to self-employment. The right plot shows that there is no such relation for non-eligible unemployed individuals.

Figure 3. Average quarterly gross flow toward self-employment among the unemployed individuals

(a) Panel B: regular UI generosity (*Max Regular* UI_{st}) for the 1994:2007 period



(b) Panel C: regular and extended UI generosity (*Max Extended* UI_{st}) for the 2008:2015 period



Notes: aggregate gross flow rates, for individuals experiencing a layoff in the left panels and other unemployed individuals in the right panels, are calculated from the CPS. The size of the dots refers to the number of observations.

4.1.2 Sensitivity of occupational decisions at the micro level

To further establish the relationship between UI generosity and flows to entrepreneurship, we investigate whether it holds when we control for characteristics of individuals and US states. Our identification rests on the assumption that state-level changes in regular UI generosity are independent of factors that might otherwise affect the propensity to select into entrepreneurship among the unemployed. Hsu et al. (2018) find that this assumption is also supported in the data and we confirm this in the Online Appendix 1.2 for our sample and covariates. The maximum regular UI benefits provided by a given state are not significantly related to the unemployment rate, average wage, log real gross domestic product per capita, home price growth, or other unobservable factors captured by state and year-by-month fixed effects. Concerning the use of federal extensions of UI benefits during the Great Recession, we follow Rothstein (2011) and Hsu et al. (2018) and control for the endogeneity of the EUC and EB activations by controlling flexibly for smooth cubic polynomial functions of the state's unemployment rate in the initial period of the transition. The aim is to control for the omitted variable bias arising from the specific activation rules of the EUC and the EB. Moreover, by taking the initial state unemployment rate, there is no endogeneity issue between the dependent variable, i.e. the occupational choice a quarter ahead, and the initial state unemployment rate. Finally, we identify the effect of UI generosity on occupational choices by comparing the impact of *within* state changes in UI benefits between the pool of eligible individuals unemployed after a layoff and the rest of the unemployed. We estimate the probability model:

$$\begin{aligned} \text{Unemp. to Occ.}_{ist} =& \alpha + \beta \text{UI generosity}_{st} + \gamma \text{Layoff}_{it} + \delta \text{UI generosity}_{st} \times \text{Layoff}_{it} \\ &+ \boldsymbol{\xi} \mathbf{X}_{it} + \boldsymbol{\eta} \mathbf{Z}_{st} + \boldsymbol{\lambda}_s + \boldsymbol{\mu}_t + \epsilon_{ist} \end{aligned} \tag{16}$$

where $\text{Unemp. to Occ.}_{ist}$ is an indicator of whether individual i in state s and quarter t is switching to the following specific occupation: Self-Employment (SE) or Worker (W). The variable $\text{UI generosity}_{st}$ depends on the specification: $\log(Max\ Regular\ UI_{st})$ for regular benefits or $\log(Max\ Extended\ UI_{st})$ for regular and extended benefits. $\mathbf{X}_{it}$ is a vector of individual characteristics that includes household income brackets, educational attainment, ethnicity, sex, age, age squared, marital status, cubic polynomial in unemployment duration, and an indicator of whether the spouse is currently employed. $\mathbf{Z}_{st}$ is a vector of time-varying US states characteristics that includes a cubic in the monthly seasonally adjusted state unemployment rate, annual state log real GDP per capita, log income per capita and a housing price index. Again, those elements aim to capture the activation threshold of the UI extensions and serve as controls as the incentive to start a business might be correlated with the economic environment. Finally, λ_s and μ_t are states and year fixed effects and ϵ_{ist} is an error term.

Table. 5. UI generosity and exit probability toward an occupation.

	Panel A (1994:IV-2015:IV)							
	OLS UtoSE (1)	*OLS* UtoW (2)	*mLogit* UtoSE (3)	*mLogit* UtoW (4)	*OLS* UtoSE (5)	*OLS* UtoW (6)	*mLogit* UtoSE (7)	*mLogit* UtoW (8)
layoff	5.919***	0.356	3.272**	0.846**	−1.742***	1.052***	1.824**	0.660***
	(1.140)	(0.540)	(1.499)	(0.418)	(0.579)	(0.156)	(0.770)	(0.211)
log(*Max Reg. UI*)	−0.067	0.003	−0.110	0.048				
	(0.150)	(0.060)	(0.240)	(0.066)				
layoff x log(*Max Reg. UI*)	−0.647***	−0.010	−0.363**	−0.077*				
	(0.120)	(0.058)	(0.162)	(0.045)				
log(*Max Ext. UI*)					−0.115	0.057	−0.035	0.082
					(0.155)	(0.048)	(0.193)	(0.053)
layoff x log(*Max Ext. UI*)					−0.189***	−0.085***	−0.200**	−0.056***
					(0.056)	(0.016)	(0.080)	(0.022)
Observations	140,952							
	Panel B (1994:IV-2007:IV)				Panel C (2008:I-2015:IV)			
	OLS UtoSE (9)	*OLS* UtoW (10)	*mLogit* UtoSE (11)	*mLogit* UtoW (12)	*OLS* UtoSE (13)	*OLS* UtoW (14)	*mLogit* UtoSE (15)	*mLogit* UtoW (16)
layoff	5.080**	0.460	5.280**	1.158*	2.575***	1.100***	3.122***	0.996***
	(2.347)	(0.429)	(2.214)	(0.644)	(0.738)	(0.249)	(1.192)	(0.305)
log(*Max Reg. UI*)	0.079	−0.107	0.003	−0.237*				
	(0.370)	(0.073)	(0.432)	(0.129)				
layoff x log(*Max Reg. UI*)	−0.552**	−0.024	−0.586**	−0.114				
	(0.250)	(0.046)	(0.239)	(0.070)				
log(*Max Ext. UI*)					0.018	0.034	0.096	0.033
					(0.268)	(0.040)	(0.314)	(0.079)
layoff x log(*Max Ext. UI*)					−0.256***	−0.087***	−0.319***	−0.088***
					(0.071)	(0.024)	(0.118)	(0.030)
Observations	72,112	72,112	72,112	72,112	68,840	68,840	68,840	68,840
State and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. & state controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors, adjusted for clustering at the state level, are reported in parentheses. See text for the list of controls. OLS estimates are normalized by the mean transition rate of the flow, and can be interpreted as an elasticity relative to that mean transition rate.

The results for Panel A (1994:2015) are reported in Table 5 (top) both for OLS and multinomial Logit specifications.[25] The latter takes the remaining unemployed as a reference and also consider other flows out of the labor force. The effect of the generosity of regular UI benefits (columns (1)-(4)) and extended UI benefits (columns (5)-(8)) on the propensity to switch to entrepreneurship among the laid-off workers relative to other unemployed individuals is significant and negative. To get a sense of the magnitude of the effect, given the estimates in column (1) (resp. column (5)), a 1000$ increase of *Max Regular UI* is associated with a signif-

[25] In the OLS specification, the Unemp. to Occ.$_{ist}$ variable is divided by the average transition rate from unemployment to the specific occupation over the sample, such that our estimates will reflect the percentage point change relative to the average probability of switching.

icant 0.021 (resp. 0.006) percentage points decline in the average probability of switching to self-employment for eligible unemployed individuals.[26] Put differently, a standard deviation increase in UI benefits, i.e. a 30% increase in average generosity, would lead to a 7.4% (resp. 2.2%) decline in the fraction of insured unemployed individuals moving to self-employment. The magnitude of the corresponding number for a flow toward employment is 3 to 6 times lower. Finally, the Logit specification corroborates the previous findings and magnitude. Table 5 (bottom) distinguishes the effects of UI generosity for Panels B (pre-recession period) and C (Great Recession period). Columns (9)-(16) show that for both periods and sources of variations, extensions, or regular benefits adjustments, UI generosity has a negative and significant effect on the propensity to select into entrepreneurship. The effect is larger during the pre-recession period, in which the source of variations is mainly due to a change in the weekly benefit amount (WBA). These results are robust to a variety of alternative specifications that we report in Appendix A.1. Notably, the results hold for an alternative definition of entrepreneurship based on self-employment *and* business ownership and for alternative UI generosity measures, controls, and sample periods.

The results above show that there is an economically significant and large empirical relation between UI provision and the probability that unemployed individuals select into entrepreneurship. This channel has a significant impact on gross labor market flows.

4.2 Responsiveness to UI Generosity: Model

We now use our quantitative model to assess the responsiveness of gross labor market flows to UI generosity. We first characterize the effects on gross flows and in turn the effects on occupational masses and aggregate outcomes in a general equilibrium context.

Our investigations are based on counterfactual stationary economies under alternative UI designs with varying levels of generosity. In the model, total UI generosity is defined by: (i) a maximum duration $\overline{J}$ (this is a bimonthly variable in the model but, for clarity's sake, we express it in weeks equivalent hereafter), (ii) a replacement rate μ, and (iii) a maximum benefit amount $\overline{b}$. To analyze the effects of alternative UI designs, we use the following approach. We run a sufficiently large number of counterfactual deviations from our baseline economy in which the parameters governing the maximum duration $\overline{J}$, the replacement rate μ and the maximum UI benefit amount $\overline{b}$ are uniformly drawn, such that the model variations in those

[26] Note that a 1000$ increase of UI corresponds to an increase of 3.2% of the average *Max Regular UI*. Therefore, in Panel A, the percentage point number corresponds to -0.65*3.2/100 (resp. -0.19*3.2/100).

statistics fall in the range of the variations observed across US states and over time, including UI extensions. The replacement rate varies from 30% to 50%, the duration varies from 16 to 99 weeks, and the maximum UI benefit amount varies from 25% to 60% of the mean wage. The generosity of the UI benefits is given by:

$$\text{UI max} = C_{adjust} \sum_{j=0}^{\bar{J}} b(\bar{\vartheta}, j) = C_{adjust}(1-\tau) \min\left\{ wh(\bar{\vartheta})\mu, \bar{b} \right\} \times \bar{J}, \qquad \bar{\vartheta} = \int_{\mathbf{x}} \vartheta d\Gamma(\mathbf{x}), \tag{17}$$

where $\bar{\vartheta}$ captures the average ability level in the economy and $C_{adjust} = \frac{\text{Data wealth median}}{\text{Model wealth median}}$ rescales nominal values in the model relative to the data.

4.2.1 Effects of UI generosity on Occupational Choices

Using observations from the sample of counterfactual experiments, we estimate the elasticity of the flow from a given occupation to another with respect to a variation in UI generosity. To this end, we run the following model-based specification:

$$\log(f_{X \to Y})_i = \varepsilon_{X \to Y} \log(\text{UI max})_i + err_i, \qquad (X, Y) \in \{E, U_I, U_N, W\}, \tag{18}$$

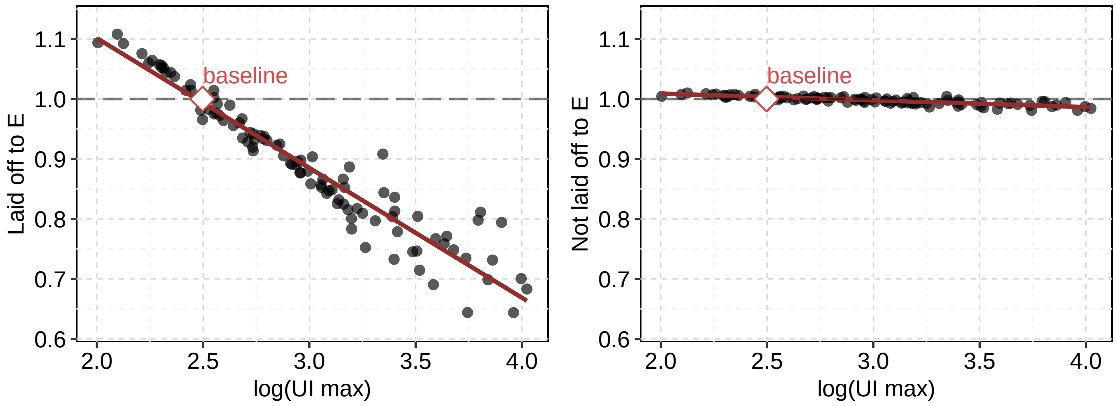
with X any occupation out of which the flow $f_{X \to Y}$ is originating and Y the destination occupation. Additionally, note that similarly to the data section, we separate the insured unemployment pool U_I from the uninsured pool U_N. $\varepsilon_{X \to Y}$ defines the occupational flow elasticity to UI generosity, i.e. the percentage change in the likelihood to switch to a specific occupation Y out of the occupation X when UI generosity varies by 1%. For instance, $\varepsilon_{U_I \to E}$ is the elasticity of the flow from insured unemployment to entrepreneurship with respect to UI generosity.

As the elasticity $\varepsilon_{X \to Y}$ measures the effects of UI generosity on individual occupational choices using aggregate flows in the model, it is important to rule out any composition effects.[27] To control for this, we estimate equation (18) using the stationary distribution of the economy under our baseline UI parameters. To be concrete, agents in this stationary equilibrium face an unanticipated UI shock corresponding to the specific counterfactual $\{\bar{J}, \mu, \bar{b}\}$ set. We then capture the change in the average flow from a given pool of individuals, i.e. $f_{X \to Y}$, arising from variations in search intensities and decisions to switch while keeping the population, prices, and taxes unchanged.

[27] It is important that the initial distribution of agents remains the same across counterfactuals as otherwise wealth profiles and abilities along the distribution will certainly bias the estimate: depending on wealth and ability, individuals might be more sensitive to UI variations, conditioning the impact we are measuring. In the Online Appendix 2.1 we provide a second metric using the counterfactual long run steady-state masses that yield long run elasticities. The virtue of this measure of elasticities is that it better captures long run GE adjustments. The drawback is that it is based on different population masses in each occupation.

Selection out of unemployment Figure 4 shows the model-based change in the flow $f_{U \to E}$ from insured (left panel) and uninsured (right panel) unemployment to entrepreneurship. The patterns from unemployment to entrepreneurship are remarkably close to the empirical patterns reported in Figure 3a and Figure 3b. The slope of the occupational flow from insured unemployment to entrepreneurship is linear (in log) in UI generosity and is significantly decreasing. Looking at point estimates in Table 6, it is noticeably steeper than the slope from insured unemployed to employment. The corresponding elasticities, $\varepsilon_{U_I \to E}$ and $\varepsilon_{U_I \to W}$, are again remarkably close to our empirical estimates. In contrast, the elasticities out of the uninsured unemployed pool show no sensitivity to UI generosity: this pool is only slightly less likely to start a business.[28]

Figure 4. UI generosity and model average flows from the insured and uninsured unemployed pools.



Note: the red square marks the current average regular UI provision in the US, with $\mu = 0.45$, $\bar{J} = 26$ weeks, and $\bar{b} = 50\%$ of mean wage. The maximum UI generosity here is $\mu = 0.498$, $\bar{J} = 99$ weeks, and $\bar{b} = 60\%$ of mean wage.

Table. 6. Elasticity of unemployment flows to UI generosity: model and data

Elasticity $\varepsilon_{X \to Y}$	Data[a]		Model		Model (no monitoring)	
	U to E	U to W	U to E	U to W	U to E	U to W
Insured unemp. workers	-0.200^{**}	-0.056^{***}	-0.247^{***}	-0.044^{***}	-0.346^{***}	-0.214^{***}
	(0.080)	(0.022)	(0.008)	(0.001)	(0.010)	(0.008)
Uninsured unemp. workers	-0.035	0.082	-0.011^{***}	0.001^{***}	-0.027^{***}	0.003^{***}
	(0.193)	(0.053)	(0.000)	(0.000)	(0.001)	(0.000)

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses.
[a] Estimates for the data are taken from the mLogit results in Table 5.

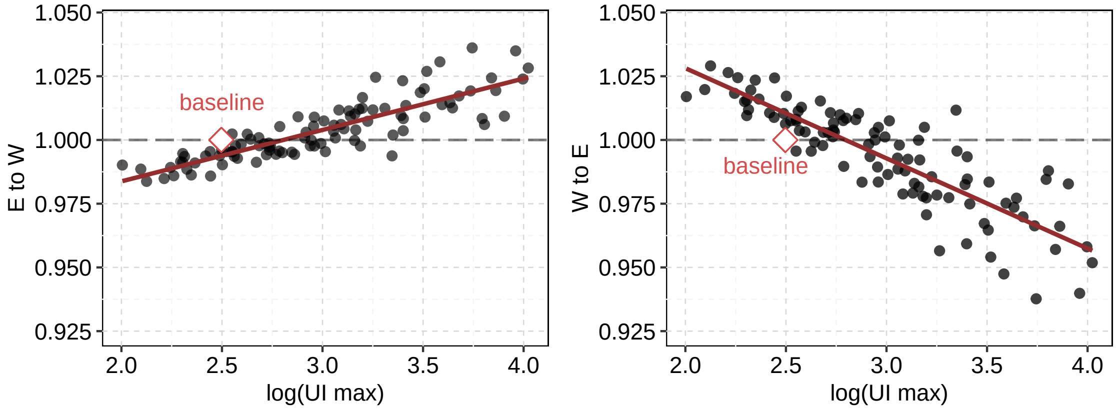
Additionally, due to the monitoring of program applicants, UI agencies enforce regular job search efforts at the expense of the efforts to start a business. While this channel has been investigated in Hansen and Imrohoroğlu (1992), we quantitatively verify its importance in our setup where it is captured by the probability $\pi^m(s_w)$. To get a sense of the magnitude of this ef-

[28]In Table 8 (4th and 5th row) of Appendix A.1, we show that separately using the amount of UI benefits and UI duration generates different estimates in the data, that our model can account for quite well.

fect, we run our counterfactual experiments in an alternative specification without monitoring. We find that the sensitivities of gross flows from insured unemployment to both employment and entrepreneurship are magnitudes higher and imply resulting elasticities $\varepsilon_{U_I \to E} = -0.346$ and $\varepsilon_{U_I \to W} = -0.214$. Therefore, our monitoring feature, despite its stylized nature, helps in producing the observed lower sensitivity of these flows as estimated in Table 5.

Selection out of employment and entrepreneurship In the case of the gross flows between entrepreneurship and employment, we find that $\varepsilon_{W \to E} = -0.036$ and $\varepsilon_{E \to W} = 0.020$ and illustrate the resulting slopes in Figure 5. A consequence of the magnitude of these elasticities is that changes in occupational choices *on-the-business* and *on-the-job* following a change in UI generosity are likely to have long run implications on occupational masses alongside the large and direct effect on unemployed individuals. We further discuss these elements in Section 4.2.2. In Appendix A.1, we provide an empirical support for these additional selections *on-the-job* and *on-the-business*.

Figure 5. UI generosity and model average flows between entrepreneurship and employment.



Note: the red square marks the current average regular UI provision in the US, with $\mu = 0.45$, $\bar{J} = 26$ weeks, and $\bar{b} = 50\%$ of mean wage. The maximum UI generosity here is $\mu = 0.498$, $\bar{J} = 99$ weeks, and $\bar{b} = 60\%$ of mean wage.

Selection by ability and wealth Increasing UI benefits has a disproportionate impact on particular groups of individuals in our economy. Table 7 displays the decomposition by ability and wealth of elasticities $\varepsilon_{U_I \to E}$ and $\varepsilon_{U_I \to W}$. First, it is noticeable that $\varepsilon_{U_I \to E}$ is less responsive with ability and is almost flat for $\varepsilon_{U_I \to W}$. Second, for both elasticities, wealth poor individuals (relative to the median) have a stronger response than wealthier ones.

The decomposition by wealth is straightforward. On the one hand, and related to the *liquidity effect* in Chetty (2008), wealth-poor individuals are closer to the liquidity constraint and are therefore more sensitive to variations in UI generosity. On the other hand, a higher wealth level lets prospective entrepreneurs run larger and more valuable firms. Again, wealth-poor

Table. 7. Model-based elasticity of insured unemployment to UI generosity by ability and wealth.

Elasticity $\varepsilon_{X\to Y}$	Ability			Net worth	
	$\vartheta = \vartheta_1$	$\vartheta = \vartheta_2$	$\vartheta = \vartheta_3$	$a <$ median	$a \geq$ median
$\varepsilon_{U_I\to E}$	-0.291^{***}	-0.265^{***}	-0.155^{***}	-0.356^{***}	-0.109^{***}
	(0.011)	(0.008)	(0.013)	(0.013)	(0.008)
$\varepsilon_{U_I\to W}$	-0.045^{***}	-0.045^{***}	-0.039^{***}	-0.028^{***}	0.009
	(0.002)	(0.001)	(0.003)	(0.005)	(0.006)

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in parentheses.

individuals have a smaller incentive to start a business. As a consequence, the combination of this incentive and the *liquidity effect* makes wealth-poor individuals (below the median) 3 times more responsive to UI generosity when trying to start a business than wealth-rich individuals (above the median). Therefore, the presence of a credit constraint plays an especially important role in understanding the high elasticity of wealth-poor prospective entrepreneurs as investment capability is a key requirement for a valuable business.

Regarding the decomposition by ability ϑ, low ability individuals are on average poorer than higher ability ones. Thus, the liquidity and threshold effects of more UI generosity are stronger for those agents. This explains the decreasing responsiveness of $\varepsilon_{U_I\to E}$ with ability. We do not find, however, that the responsiveness of the gross flows from insured unemployment to employment, $\varepsilon_{U_I\to W}$, differ much by ability. This is due to the effect of monitoring which induces unemployed agents to provide a sufficient amount of job search effort. In an alternative specification without monitoring, the corresponding elasticity becomes less responsive with ability and similar to what is obtained here with the gross flows toward entrepreneurship.

Mechanisms Our elasticities results substantiate the idea that higher UI generosity lowers the incentives to exit insured unemployment. Two well-known effects support this interpretation: (i) a *moral hazard effect* which captures the change in the marginal incentive to search following a variation in UI benefits that effectively lowers the expected net income gain of taking a job; (ii) the above-mentioned *liquidity effect*, previously discussed in Browning and Crossley (2001) and Chetty (2008), which captures the variation of the search effort with respect to the loosening of the liquidity constraint following a change in UI generosity. Specifically, for a given level of wealth, the *liquidity effect* is the effect of an extra amount of wealth coming from more UI generosity. This extra amount relaxes the effect of the borrowing constraint and helps with consumption smoothing, thereby lowering the incentive to exit insured unemployment.

On top of those effects, additional considerations appear when analyzing the impact of UI generosity in an entrepreneurial context. As entrepreneurs are not part of the UI system, the value of entrepreneurship is not responsive to an increase in UI generosity, at least not directly, and $\frac{\partial E}{\partial b} \approx 0$ in the current and future periods. As a consequence, insured unemployed individuals significantly reduce their business search effort s_e relative to their job search effort s_w. We view this as an *insurance coverage effect*: relative to a variation in UI generosity, it is the change in the relative riskiness between two asymmetrically covered occupations leading to a change in the incentive to choose one or the other activity. The distance between the entrepreneurial and unemployment values is substantially affected by the change in UI generosity (i.e. $(E - U_I') \ll (E - U_I)$), while the distance between employment and unemployment values is less affected (i.e. $(W' - U_I') < (W - U_I)$), due to the asymmetric UI coverage between employment and entrepreneurship. Therefore, the business search effort of insured unemployed individuals is likely to be more sensitive to a change in the UI relative to the job search effort. The *insurance coverage effect* also concerns the gross flows between employment and entrepreneurship: the risk of a job loss is covered by UI whereas the loss of a self-employed activity is uninsured. As a consequence, the higher the UI generosity, the higher the opportunity cost associated with a self-employment activity relative to employment.[29]

Those results demonstrate that variations in UI generosity have consequences beyond the direct effects on the pool of unemployed individuals and concern gross flows in and out of entrepreneurship and employment in general.

4.2.2 Long Run Occupational Masses

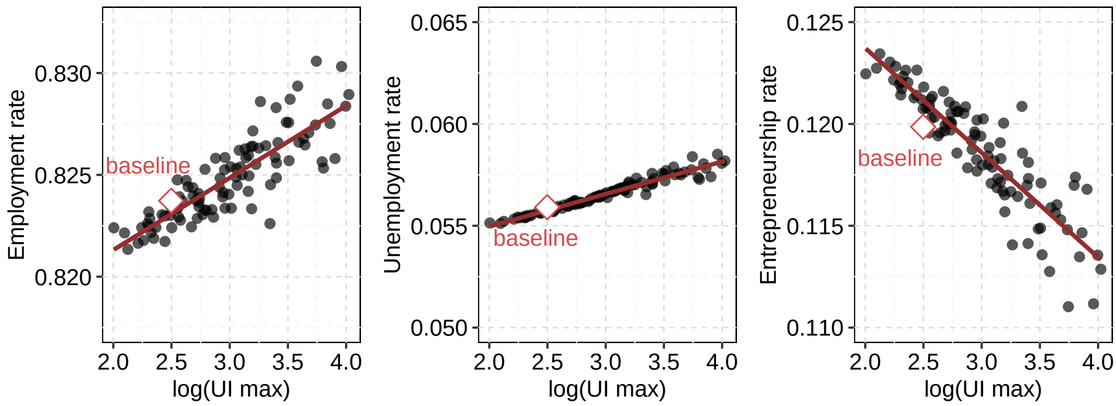
Our model has also additional implications on the long run aggregate masses of individuals in each occupation. To capture this, we compute the long run stationary equilibrium induced by the change in UI generosity in each counterfactual experiment. This analysis provides a characterization of the long run status of the labor market once all transitional adjustments are completed and equilibrium prices are adjusted. This is valuable because the resulting masses are difficult to predict using only information concerning gross flows since the relative mass of individuals in each occupation is different. For instance, even though unemployed agents might have a strong response to a change in the UI, they only represent 5% to 6% of individuals in the model. In contrast, workers account for around 82% to 83% of the population, but, as discussed previously, they react much less to UI variations. The resulting occupational masses are therefore *a priori* ambiguous.

[29] A similar argument is given in Fuchs-Schündeln and Schündeln (2005): they show that people with lower risk aversion select into civil service occupations. In our paper, the degree of employment coverage distorts the relative riskiness of self-employment relative to employment, which modifies the selection into those occupations.

In Figure 6, we display the long run invariant mass of individuals in each occupation. We find that the employment rate is increasing with UI generosity in the long run, with an elasticity of 0.004. However, it is the masses of entrepreneurs and unemployed individuals that are the most affected (in relative terms) with long run elasticities of the mass to UI generosity of respectively -0.044 and 0.028. To put this into perspective, a doubling of UI generosity relative to the baseline value would increase the unemployment rate by 0.11 percentage points and decrease the entrepreneurship rate by 0.36 percentage points.

We stress that the patterns discussed above remain robust even when general equilibrium adjustments are neutralized, for instance by fixing prices to the ones in our baseline stationary equilibrium. Our results point out that UI generosity has a particularly large effect on entrepreneurship in the long run. Moreover, if one was to consider total employment as the addition of both self-employment and employment, UI generosity would have a negative and significant effect on this aggregate variable in the model.

Figure 6. UI generosity and occupational masses.



Note: the red square marks the current average regular UI provision in the US, with $\mu = 0.45$, $\overline{J} = 26$ weeks, and $\overline{b} = 50\%$ of mean wage. The maximum UI generosity here is $\mu = 0.498$, $\overline{J} = 99$ weeks, and $\overline{b} = 60\%$ of mean wage.

Relating our findings to the existing literature is instructive. On the one hand, and as shown by the above results, occupational flows, especially out of insured unemployment, are consistent with those established in the literature and supported by liquidity and moral hazard effects. Notably, UI generosity has a depressing effect on the flow from insured unemployment. On the other hand, another strand of the literature, for instance, Chodorow-Reich et al. (2019) and Boone et al. (Forthcoming), empirically find a small (and non-significant) effect of UI generosity on the aggregate level of employment (in relative terms). This observed disconnect between micro-level transitions from unemployment to employment and the resulting aggregate employment are hard to reconcile.[30] We show that when taking into account self-employment, adjustment at the micro-level might not reflect adjustment at the macro-level. In the long run, the employment rate increases in our setup with UI generosity because individuals are less likely to enter self-employment and are more likely to exit self-employment.

4.2.3 UI Generosity and Long Run Aggregate Outcomes

We now discuss the effects of UI generosity on long run macro aggregates. As the mass of entrepreneurs decreases, the long run entrepreneurial sector output Y^E and capital K^E are significantly reduced. Conversely, as the mass of workers and aggregate corporate capital remains nearly constant, aggregate corporate output Y is only slightly impacted. Perhaps surprisingly, the average firm size increases with higher UI generosity. As discussed earlier, this is related to the fact that the incentives to create a business and remain self-employed are higher for wealth-rich individuals when employment becomes relatively better insured.

Additionally, a higher level of UI generosity reduces precautionary savings overall while selecting wealthier entrepreneurs. Together, these effects lead the ratio of median net worth between entrepreneurs and the rest of the population to rise with UI generosity. Overall, most of the striking effects appear on entrepreneurial margins.

In Appendix A.2, we perform robustness analyses regarding the question of the financing of UI and various sensitivity analyses on the modeling assumptions and parameter choices.

5 Accounting for Gross Flows during the Great Recession

As an additional test of the model's implications, we now explore how gross labor market flows within our model react to a change in the labor market conditions and to temporary variations in UI during the Great Recession (GR). During this period, we highlight large changes in gross flows together with special UI extensions: starting in late 2008, the UI extensions (the EB and EUC programs) were activated for about 5 years. Our aim is to quantitatively evaluate the repercussion on occupational masses and to decompose the effects. We do not, however, aim to explain the recession *per-se*.

[30]For instance, Boone et al. (Forthcoming) argues that a demand channel following an increase in UI benefits could generate an increase in the aggregate employment rate and dampen the negative effect from micro disincentives. Concerning recent empirical findings with small micro disincentive effects on the job-finding rate, Farber et al. (2015) study the effects of UI extensions during the Great Recession and find little or no effect on job-finding but a reduction in labor force exits due to benefit availability.

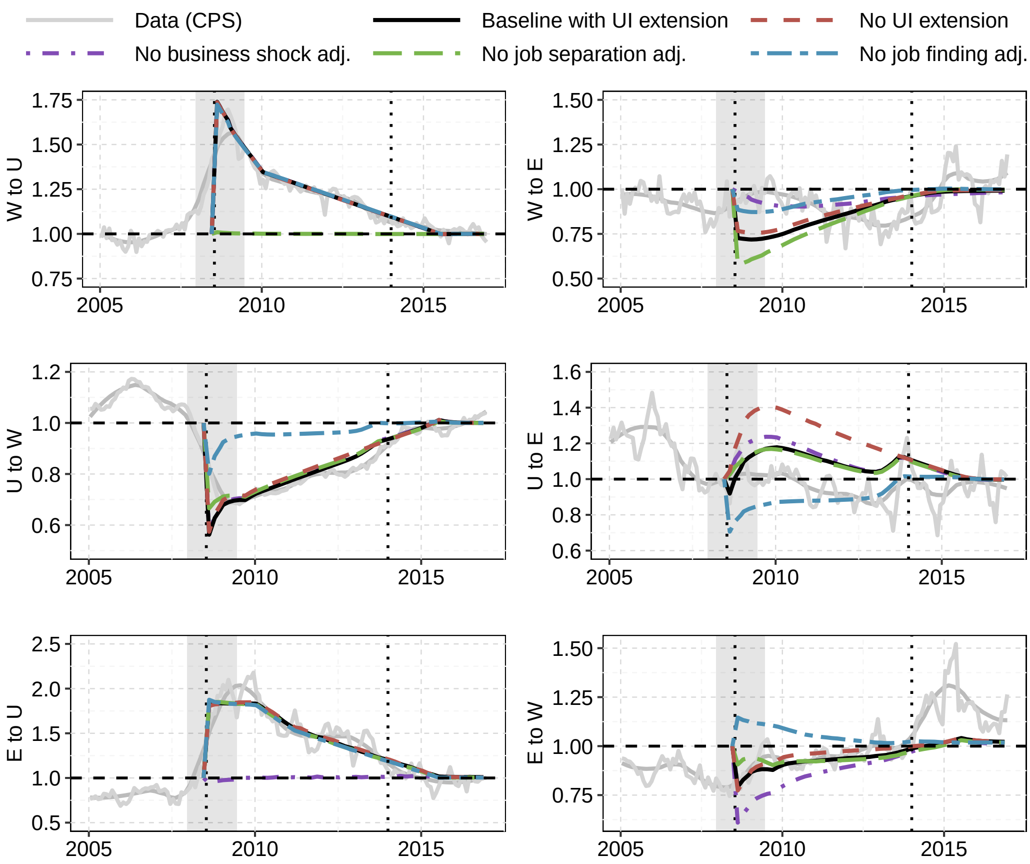
Our GR experiment is based on transitional dynamics and is similar to an MIT shock approach. The separation rate, the job-finding rate, and the process of the business shock z are changed over time in addition to the duration of UI. All these changes are revealed at time $t = 1$ leading to a perfect-foresight transition path.[31] We manipulate the set of parameters $\{\eta(\vartheta), \kappa_w, p_{z0}, \bar{J}\}$ to consistently account for the data. First, we implement in mid-2008 until the end of 2013 an UI extension replicating the average EB and EUC08 extensions: the UI duration $\bar{J}$ is increased to 76 weeks during this period. The job separation shock $\eta(\vartheta)$ and the job finding elasticity κ_w are adjusted to replicate the job separation and finding rate in the CPS during the GR. Finally, we adjust p_{z_0} to fit the increasing gross flows from entrepreneurship toward unemployment during this period. Appendix A.2.2 shows the change in the parameters of interest. Figure 7 shows the flows across occupations during the GR. The model dynamics (in black) are broadly consistent with the data patterns (in grey) with one caveat. There is a reduction in the early transition from employment to entrepreneurship which seems to be observed in the data only in mid-2012. Apart from this flow and the three targeted flows ($f_{U \to W}$, $f_{E \to U}$ and $f_{W \to W}$), the adjustments of $f_{E \to W}$ and $f_{U \to E}$ are consistent with what is observed in the CPS. Notice that the setting without UI extensions (dashed red) generates a much higher response of $f_{U \to E}$ relative to what was actually observed. This will in turn have non-negligible effects on occupational masses.

To provide a tractable quantification of the contribution of each component, including UI extensions, on the gross labor markets flows, we run a counterfactual experiment in which, *ceteris paribus*, we fix one of the four components in $\{\eta(\vartheta), \kappa_w, p_{z0}, \bar{J}\}$ to their benchmark value. Figure 8 displays the resulting occupational masses and the entrepreneurial sector GDP.

As the entrepreneurship rate is known to be decreasing since the 80s, we detrend all the series linearly. We find that each component has a significant effect on the resulting occupational stocks. It is interesting to note that without the change in p_{z_0}, the entrepreneurship rate is increasing during the GR. First, employment is riskier because of the increased job separation rate, changing the relative riskiness of self-employment and leading to a surge in the flow into entrepreneurship. Second, as unemployed individuals are more likely to switch to self-employment (see Table 1), there is a mechanical effect that pushes toward higher flows to self-employment. Together, those two effects contribute to a higher entrepreneurship rate

[31] Although conceptually more satisfactory, it is computationally more challenging to consider model expectations over shocks and gradually reveal policy changes. We acknowledge it is a limit of our experiment but we are not at odds with the literature on this point.

Figure 7. Transitions between occupations during the Great Recession.

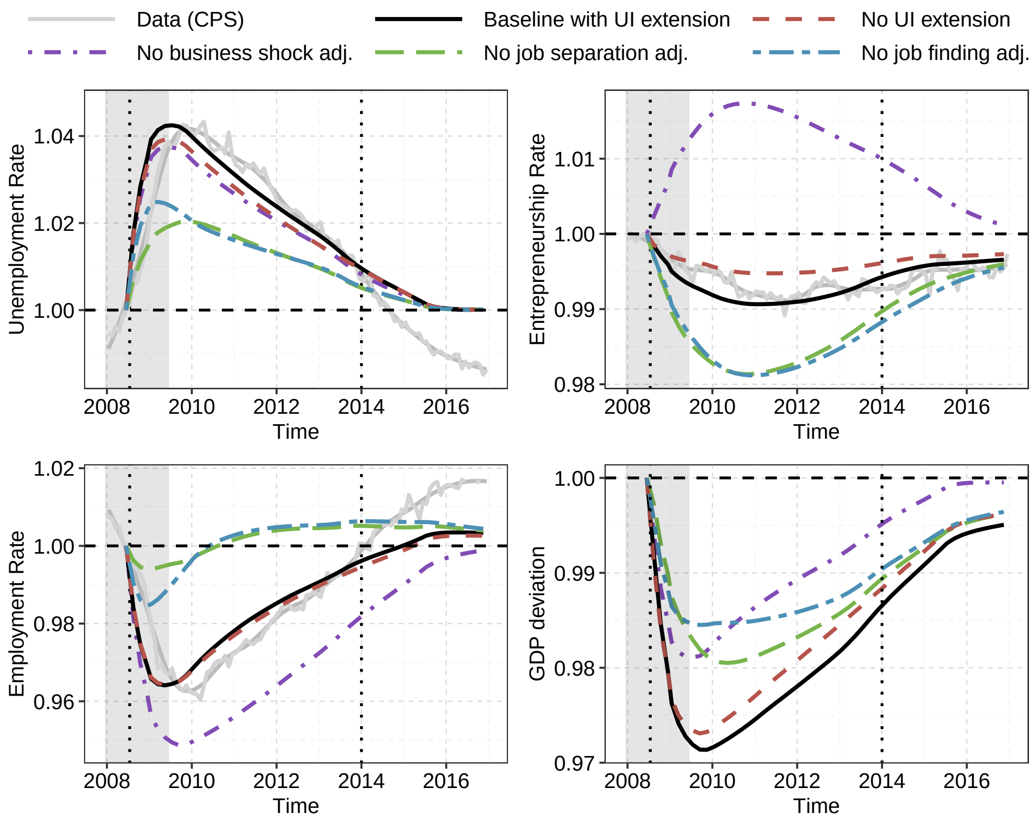


Notes: Grey area: NBER definition of the GR. Vertical dotted line: EUC and EB implementation dates, from mid-2008 to end-2013. The solid grey line is the smoothed CPS data.

and a lower entrepreneurial exit rate such that p_{z_0} is needed to counterbalance them. The adjustments of the job separation and the job-finding rates work in the same direction: they contribute to the overall increase in the unemployment rate and to the decrease in the employment rate. Without those two adjustments, the unemployment rate would have been larger (again, due to a composition effect), which would have decreased the selection into entrepreneurship, and, thus, the drop in the entrepreneurship rate would have been even larger. Finally, notice that the decrease in the entrepreneurship rate is quite persistent as finding a business to run is a slow process. Even after all shocks have vanished, and consistent with the CPS data, the self-employment rate is below its long run steady-state value.

Concerning the adjustment of UI extensions, we find that they have a non-negligible impact on occupational flows and therefore on occupational stocks. As expected, and echoing Nakajima (2012), the extensions increases the unemployment rate. Comparing the models with and without the extensions, we find a difference of about 0.3-0.35 percentage points in 2010:2011

Figure 8. UI change during the Great Recession.



Notes: Grey area: NBER definition of the GR. Vertical dotted line: EUC and EB implementation from mid-2008 to end-2013. The occupational rates are computed using the CPS and are detrended. The solid grey line is the smoothed CPS data. We normalize the rates by their starting value in December 2007 such that the occupational rates are in deviations from their starting values.

that persists until the end of the EB and EUC programs. In line with our previous findings, those extensions also decrease the entrepreneurship entry rate and thus the entrepreneurship rate by about 0.4-0.45 percentage points in 2010:2011. This, however, leads to only a marginal impact on the employment rate consistent with our previous findings. This reallocation effect mechanically translates into a lower GDP as the number of entrepreneurs decreases.

6 Conclusion

This paper introduces a parsimonious model of gross labor market flows between employment, unemployment, and entrepreneurship. Our benchmark economy produces an empirically accurate characterization of US aggregate gross labor market flows while accounting for the micro-level decisions that support them. Notably, the model produces an adequate fit of gross flows conditional on individual state variables, in particular by wealth and ability.

Our analysis clarifies the contribution of key factors in generating the observed labor market dynamics. Search frictions across all occupations play an important role and the possibility to search for a business opportunity both when unemployed and *on-the-job* provides a plausible and important margin. A second factor is the nature of the entrepreneurial production technology which lets entrepreneurs use only their own labor to produce. Those features are used to characterize the observed flows, especially those of self-employed individuals creating low to zero capital businesses.

Our analysis also characterizes the responsiveness of gross labor market flows to a typical change in UI generosity. We empirically find a negative and significant relation between UI generosity and the propensity for eligible unemployed individuals to select into entrepreneurship, which is an order of magnitude larger than the one from unemployment to employment. Our benchmark model is able to generate this empirical responsiveness. One implication is that reallocations of individuals from entrepreneurship to employment following an increase in UI generosity lead to a faintly increasing aggregate employment rate, providing a channel to explain its observed irresponsiveness to UI variations.

Finally, we use our model to decompose the contribution of various changes in labor market conditions and the implementation of UI extensions that generated large shifts in occupational masses during the Great Recession. Notably, we evaluate the impact of UI extensions during that period to have reduced self-employment by 0.45 percentage points.

References

Agrawal, A.K., Matsa, D.A., 2013. Labor unemployment risk and corporate financing decisions. Journal of Financial Economics 108, 449–470.

Ali, A., Allen, I.E., Brush, C., Bygrave, W.D., De Castro, J., Lange, J., Neck, H., Onochie, J., Phinisee, I., Rogoff, E., Suhu, A., 2008. What Entrepreneurs Are Up To. Technical Report. Global Entrepreneurship Monitor.

Anderson, P.M., Meyer, B.D., 2000. The effects of the unemployment insurance payroll tax on wages, employment, claims and denials. Journal of Public Economics 78, 81–106.

Asenjo, A., Pignatti, C., et al., 2019. Unemployment insurance schemes around the world: Evidence and policy options. International Labour Office.

Astebro, T., Chen, J., 2014. The entrepreneurial earnings puzzle: Mismeasurement or real? Journal of Business Venturing 29, 88–105.

Been, J., Rohwedder, S., Hurd, M., 2020. Does home production replace consumption spending? Evidence from shocks in housing wealth in the Great Recession. Review of Economics and Statistics 102, 113–128.

Boone, C., Dube, A., Goodman, L., Kaplan, E., Forthcoming. Unemployment insurance generosity and aggregate employment. American Economic Journal: Economic Policy .

Browning, M., Crossley, T.F., 2001. Unemployment insurance benefit levels and consumption changes. Journal of Public Economics 80, 1–23.

Brüggemann, B., Forthcoming. Higher taxes at the top: The role of entrepreneurs. American Economic Journal: Macroeconomics .

Cagetti, M., De Nardi, M., 2006. Entrepreneurship, frictions, and wealth. Journal of Political Economy 114, 835–870.

Cagetti, M., De Nardi, M., 2009. Estate taxation, entrepreneurship, and wealth. American Economic Review 99, 85–111.

Caliendo, M., Kritikos, A., 2009. "I want to, but I also need to": Start-Ups resulting from opportunity and necessity. IZA Discussion Papers 4661.

Castro, R., Clementi, G.L., Lee, Y., 2015. Cross sectoral variation in the volatility of plant level idiosyncratic shocks. The Journal of Industrial Economics 63, 1–29.

Chetty, R., 2008. Moral hazard versus liquidity and optimal unemployment insurance. Journal of Political Economy 116, 173–234.

Chodorow-Reich, G., Coglianese, J., Karabarbounis, L., 2019. The macro effects of unemployment benefit extensions: a measurement error approach. The Quarterly Journal of Economics 134, 227–279.

Clementi, G.L., Palazzo, B., 2016. Entry, exit, firm dynamics, and aggregate fluctuations. American Economic Journal: Macroeconomics 8, 1–41.

Farber, H.S., Rothstein, J., Valletta, R.G., 2015. The effect of extended unemployment insurance benefits: Evidence from the 2012-2013 phase-out. American Economic Review 105, 171–76.

Fuchs-Schündeln, N., Schündeln, M., 2005. Precautionary savings and Self-Selection: Evidence from the German reunification “experiment”. The Quarterly Journal of Economics 120, 1085–1120.

Grubb, D., 2001. Eligibility criteria for unemployment benefits. Labour Market Policies and Public Employment Service .

Hamilton, B.H., 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. Journal of Political economy 108, 604–631.

Hansen, G.D., Imrohoroğlu, A., 1992. The role of unemployment insurance in an economy with liquidity constraints and moral hazard. Journal of Political Economy 100, 118–142.

Herranz, N., Krasa, S., Villamil, A.P., 2015. Entrepreneurs, risk aversion, and dynamic firms. Journal of Political Economy 123, 1133 – 1176.

Hombert, J., Schoar, A., Sraer, D., Thesmar, D., 2020. Can unemployment insurance spur entrepreneurial activity? Evidence from France. The Journal of Finance 75, 1247–1285.

Hsu, J.W., Matsa, D.A., Melzer, B.T., 2018. Unemployment insurance as a housing market stabilizer. American Economic Review 108, 49–81.

Hurst, E., Lusardi, A., 2004. Liquidity constraints, household wealth, and entrepreneurship. Journal of political Economy 112, 319–347.

Kitao, S., 2008. Entrepreneurship, taxation and capital investment. Review of Economic Dynamics 11, 44–69.

Krusell, P., Mukoyama, T., Rogerson, R., Şahin, A., 2017. Gross worker flows over the business cycle. American Economic Review 107, 3447–76.

Krusell, P., Mukoyama, T., Şahin, A., 2010. Labour-market matching with precautionary savings and aggregate fluctuations. The Review of Economic Studies 77, 1477–1507.

Lentz, R., Tranaes, T., 2005. Job search and savings: Wealth effects and duration dependence.

Journal of labor Economics 23, 467–489.

Meyer, B.D., 1990. Unemployment insurance and unemployment spells. Econometrica 58, 757–782.

Moffitt, R., 1985. Unemployment insurance and the distribution of unemployment spells. Journal of Econometrics 28, 85–101.

Mortensen, D.T., Pissarides, C.A., 1994. Job creation and job destruction in the theory of unemployment. The Review of Economic Studies 61, 397–415.

Nakajima, M., 2012. A quantitative analysis of unemployment benefit extensions. Journal of Monetary Economics 59, 686–702.

Quadrini, V., 2000. Entrepreneurship, saving, and social mobility. Review of economic dynamics 3, 1–40.

Røed, K., Skogstrøm, J.F., 2014. Unemployment insurance and entrepreneurship. Labour 28, 430–448.

Rothstein, J., 2011. Unemployment insurance and job search in the Great Recession. Technical Report. National Bureau of Economic Research.

Wasmer, E., Weil, P., 2004. The macroeconomics of labor and credit market imperfections. American Economic Review 94, 944–963.

A Appendix

A.1 Empirical Robustness and Further Evidence

Table 8 provides robustness regarding the responsiveness of flows out of unemployment with respect to UI variations in the CPS. Alternative measures using incorporated and unincorporated self-employment (1st and 2nd rows) or self-employed business owners (3rd row) using the HUBUS CPS variable indicate that all groups react to UI extensions with especially high elasticity. We then distinguish the effects of an increase in the UI duration (4th row) and one in the weekly benefit amount (5th row). We find that change in benefit amount (WBA) has a much larger impact, a result that our model is able to rationalize: using WBA and UI duration as proxy for UI generosity gives respectively elasticities $\varepsilon_{U\to E} = -0.458$ and $\varepsilon_{U\to E} = -0.261$.

We then verify whether UI generosity is correlated with the likelihood that individuals move from employment to entrepreneurship as well as from entrepreneurship to employment. We restrict our CPS sample to the 25 to 50 years range to focus on individuals most likely to select into employment or self-employment as an alternative life prospect. As in Section 2.5.1, we run Occ_1 to $\text{Occ}_{2ist} = \alpha + \beta \log(UI\, generosity)_{st} + \boldsymbol{\xi}\mathbf{X}_{it} + \boldsymbol{\eta}\mathbf{Z}_{st} + \boldsymbol{\lambda}_s + \boldsymbol{\mu}_t + \epsilon_{ist}$ with $\text{Occ}_1 \in \{E, W\}$ and $\text{Occ}_2 \in \{E, W\}$ similar controls $\mathbf{X}_{it}$ and $\mathbf{Z}_{st}$ as in the main specification. $\boldsymbol{\lambda}_s + \boldsymbol{\mu}_t$ refers to state and time fixed effects. Table 8 (6th and 7th row) shows that, as expected, the sign of the effect of increasing UI is positive for the flow $f_{E\to W}$ and negative for $f_{W\to E}$.

Table. 8. Sensitivity analysis: main regression. [a]

	EB/EUC	U → E	U → W	E → W	W → E	S-YM FE	Period
Alternative measures & controls							
1. SE Uncorporated	Yes	-0.29^{***}	–			Yes	1994-2015
2. SE Incorporated	Yes	-0.40^{*}	–			Yes	1994-2015
3. Self-employed + bus. owners	Yes	-0.22^{***}	–			–	1994-2015
4. log(UI weeks)	Yes	-0.12^{**}	-0.12^{***}			Yes	1994-2015
5. log(UI WBA)	No	-0.59^{***}	-0.001			Yes	1994-2015
Additional specification and further evidence							
6. Selection E/W	No			0.33^{***}	-0.30^{**}	Yes	1994:2010
7. Selection E/W (WBA)	No			0.19^{*}	-0.28^{***}	Yes	1994:2010

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviations. SE clustered by US states. FE stands for fixed effects and YM stands for Year-Month and S for state. Experiments using no UI extensions use a definition of laid off unemployed individuals with less than 26 weeks in unemployment. The estimation methods are OLS. Results are robust using mLogit.

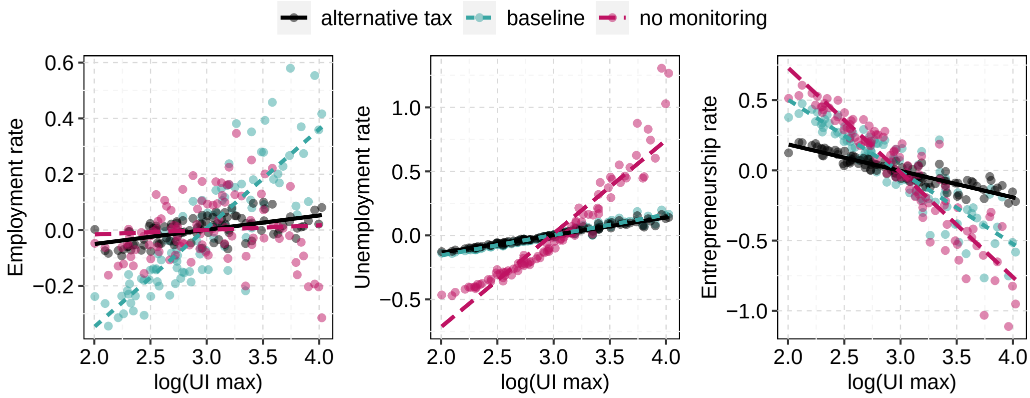
This correlation is consistent with the model, higher UI generosity leads to a reallocation of individuals from self-employment to employment.

A.2 Model Appendix

A.2.1 Robustness

UI financing The baseline economy considers the case $\tau = \tau_w = \tau_p$. This was motivated by the fact that even if regular unemployment benefits are financed by employers in the US, employees may still be indirectly facing the burden: Anderson and Meyer (2000) argue that average industry tax rates are largely passed on to workers through lower wages. Additionally, UI extensions (EUC and EB) are financed at the federal level, making it even more unclear who will eventually pay for these programs. Finally, by assuming $\tau = \tau_w = \tau_p$, we somewhat isolate the distorting effect arising from differences in occupational risk from the effect of a differential tax burden on entrepreneurs and workers. We now explore the effects of letting the workers bear the entire cost of UI, i.e. $\tau_p = 0$. In such a case, the elasticities of flows $\varepsilon_{U_I \to W}$ and $\varepsilon_{U_I \to E}$ are respectively slightly higher and lower relative to their baseline counterparts. Indeed, a higher labor income tax due to higher UI generosity changes the incentive to switch between entrepreneurship and employment relative to the benchmark because it reduces the after-tax labor income of employed individuals. Aggregating gross flows, the black dots in Figure 9 displays the resulting occupational masses under this alternative when we vary UI generosity. With a higher pass-through of the cost of UI toward workers, we find that a higher generosity induces a less positive effect on the aggregate employment rate, which becomes almost irresponsive. This also reduces the negative impact on the self-employment rate, but without overturning our result. It is noteworthy since, across US states, differing rules are applicable to the financing of UI that can extend to differences between the financing of regular UI and extensions. It also points out that economies taxing differently employers and employees when UI increases might results in differing trade-offs between occupations, especially since self-employment is not covered against the unemployment risk.

Figure 9. Percent deviation from the mean sample occupational mass for alternative specifications.



Absence of monitoring The pink dots in Figure 9 show the resulting masses in the absence of monitoring of program applicants, i.e. $\pi_m(s_w) = 1, \forall s_w$. Under this alternative, the unemployment rate is more sensitive to variations of UI generosity. This leads to a stronger reduction of the self-employment rate and to a more stable aggregate employment rate as UI varies. The main insight that entrepreneurship is highly sensitive to UI generosity remains valid.

Other robustness Non-separable disutility of search, such as $\phi \neq \psi$ with $\phi = 2.5$, produces results close to our benchmark. In particular, there is not much interaction effects between search behaviors. On the entrepreneurial side, we experimented with a high *superstar* business shock z to generate a consistent wealth distribution at the top. While matching the Gini coefficients of wealth, our results were only marginally affected. Finally, under a Cobb-Douglas assumption for the entrepreneurial production function ($p \rightarrow 0$), the responsiveness of the flow from unemployment to entrepreneurship to UI generosity is higher with $\varepsilon_{U_i \rightarrow E} = -0.321$ due to the fact that entrepreneurship becomes highly sensitive to changes in wealth.

A.2.2 Parameter change during the GR experiment

Figure 10. Parameter change during the GR experiment.