Wealth, Quits and Layoffs*

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February 28, 2023

Abstract

Using worker-level panel data we document that current wealth predicts the probability that a worker transitions from employment to non-employment. Low-wealth workers face higher probability than the median worker, but so do the high-wealth workers. This U-shaped relationship is robust to a battery of controls and suggests that wealth feeds back into the income process, creating a novel interaction between wealth and income distributions. We extend the standard incomplete markets model à la Aiyagari-Bewley-Huggett to include search frictions and jobs with heterogeneous unemployment risk and show that it can replicate our findings because i) low wealth workers optimally accept higher risk jobs in order to leave unemployment faster, and ii) high wealth workers voluntarily quit to enjoy more leisure. Accounting for the non-trivial interactions between wealth and non-employment matters for the quantification of the precautionary savings motive, wealth distribution, and wealth mobility.

Keywords: incomplete markets, job search, unemployment risk, inequality
JEL Codes: E21, J64

*Preliminary draft. We are grateful to Jan Eeckhout, Guillaume Rocheteau and seminar participants at CERGE-EI, University of East Anglia, University of Leicester and at University of California, Irvine for helpful comments.

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1 Introduction

Many countries have seen increasing income and wealth inequality in recent decades, which has been both a major concern for policymakers as well as the focus of a large academic literature. A lot of attention has been devoted so far to understanding how changes in the distribution of income impact on inequality in standards of living and on the distribution of wealth. In this paper we uncover, both empirically and quantitatively, that there is a novel, non-trivial feedback going in the opposite direction.

In particular, we make three contributions. Firstly, using worker-level panel survey data we show that current wealth predicts future non-employment risk, so that wealth inequality feeds back into the distribution of income.[1] Secondly, we show that this relationship is in fact U-shaped, with both low wealth and the highest wealth workers experiencing above average risk. To the best of our knowledge, this is a novel finding on the relationship between current wealth and future income.[2] Finally, we build a quantitative incomplete markets model which replicates these facts through worker choices, and explore its implications. We show that accounting for the non-trivial likelihood of entering non-employment is important for the measurement of the strength of the precautionary savings motive and for the mobility along the wealth distribution.

We use the Panel Study of Income Dynamics (PSID), which is a longitudinal study of households in the United States. This data provide ample information on both household wealth and labour market variables such as transitions, employment status, and wages. We investigate the relationship between current household wealth and the probability that a currently employed worker makes an employment to non-employment (EN) transition between now and the following wave of the survey.[3]

We find that workers in the middle of the wealth distribution have the lowest probability of transitioning to non-employment. As we move down the wealth distribution, the probability of making a future EN transition decreases, with the rate for the lowest wealth decile being roughly 50% higher than that of the fifth decile. However, the probability of making an EN transition is also high for the wealthiest agents, in the top wealth decile.

Then, we investigate the effect of having made an EN transition on a worker's future wealth. We find that making an EN transition leads to significant and persistent reductions in wealth for workers who experience them. The median of the cost of an EN transition is approximately one-third of wealth accumulation over a six year period, irrespective of wealth measure that we use. This cost is also approximately equal to 40% of median net wealth holdings in the cross-section.

Although we already control for likely confounding factors correlating positively with wealth, e.g., wage and age, we explore the robustness of our main result along several di-

[1] This holds for both liquid net wealth and total, i.e. less liquid, net wealth.

[2] Two plausible hypotheses both suggest an upwards sloping relationship between wealth and EN probability. The first one is a standard wealth effect hypothesis on leisure being a normal good (Algan et al., 2003; Rendon, 2006). The second one emphasizes precautionary saving considerations such that workers in higher non-employment risk jobs should save more (Larkin, 2019).

[3] We restrict our sample to workers who eventually return to the labour force, and so we exclude any transitions to permanent inactivity.

mensions. Firstly, we show that the U-shape relationship prevails not only across, but also within major demographic groups. To this end, we confirm the robustness of our main finding in sub-samples distinguished by marital status, educational attainment, gender, and age.

Secondly, in the light of our findings on adverse effects of EN transitions on wealth accumulation, we also address the issue of potential reverse causality. Indeed, if there was persistent individual heterogeneity in proneness to non-employment, the agents most likely to experience it would also be the ones with lowest wealth. We use information on past and future employment history (relative to the survey interview data) to construct adequate additional controls. The U-shaped relationship, although lessened, is found to prevail under this test as well.

We then move on to our quantitative contribution, which is to build an incomplete markets model with search frictions and heterogeneous unemployment risk. We show that the model can replicate our empirical findings, and then discuss implications and lessons from the model. The unique feature of our model is that non-employed workers can direct their search towards jobs with differing levels of unemployment risk, and that workers with different wealth levels will choose to direct their search towards different jobs.[4] We additionally incorporate a fix cost of working, which drives quit to unemployment for sufficiently wealthy workers.

The main assumption of the model is that there are two kinds of jobs: "risky" and "safe". We set up a reduced-form search problem inspired by directed search logic, where non-employed workers can only search for one kind of job at a time. Safe jobs have low unemployment risk (i.e. lower likelihood of an EN transition), but are harder to find because they have a low job offer arrival rate. Risky jobs, on the other hand, are less safe because they feature a higher likelihood of an EN transition, but are also easier to find. We abstract from wage differences across jobs, which focuses the analysis, and is also motivated by our empirical results holding conditioning on wages.

Our main quantitative finding is that the model is able to replicate the U shaped relationship between wealth and non-employment risk that we observed in the data. This occurs via two channels. Firstly, because of incomplete markets, low wealth workers search for risky but easy to find jobs in order to escape unemployment faster. This drives the left half of the U shape. Secondly, employed workers accumulate assets in order to finance quits to non-employment, so that they can enjoy temporary breaks from working. This drives the right half of the U shape. Put together, we find that reasonable parameter values are able to replicate the U shaped relationship from the data.

The model also generates dynamics for wealth in line with the data. In particular, workers run down their assets following an EN transition, as we saw in the data, and accumulate assets during employment spells. This accumulation is both due to precautionary saving against involuntary EN risk, and to finance voluntary quits. Workers in risky jobs have a higher incentive to accumulate precautionary saving, as in Larkin (2019). In his model, this drives a positive correlation between wealth and EN risk. This effect is also present in our model, as workers in the risky job accumulate assets faster than those in the safe job. However, in our

[4] This idea mirrors the directed search logic of models such as Herkenhoff et al. (2016) or Eeckhout and Sepahsalari (2021), and others in the literature review below, where non-employed workers with different wealth levels direct their search towards jobs with different wages or levels of productivity.

model this effect is dominated by the "directed search" effect (that low wealth agents search for high risk jobs) which drives the negative correlation between wealth and risk in the left half of the U, as found in the data. The model thus incorporates a "precautionary saving" effect, "wealth effect", and "directed search" effect, allowing for rich interactions between wealth and EN risk.

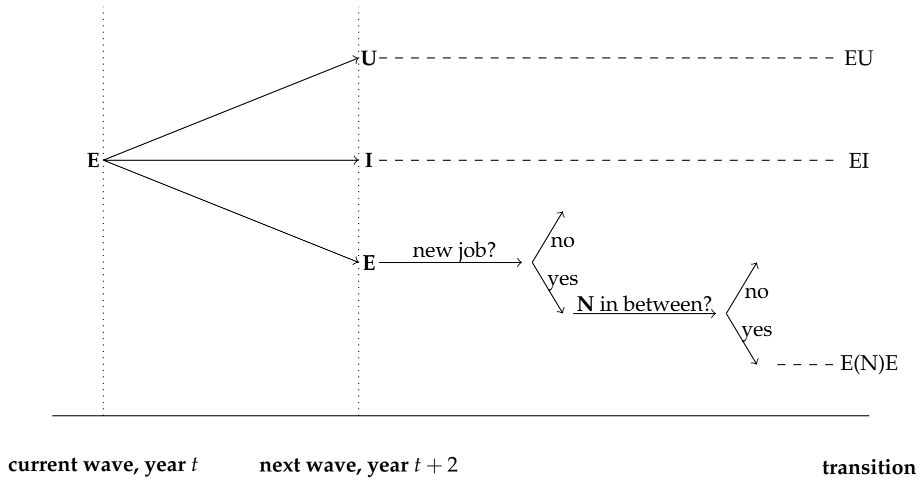
These effects interact to give new insights into the relationship between wealth inequality and income inequality and income risk. For example, relative to a standard Aiyagari model where income risk is homogeneous across jobs, the costs of incomplete markets in this model are more severe because of how income risk correlates with wealth. When income risk is homogeneous, all agents face the same level of risk, regardless of their wealth. In our model, and the data, low wealth agents have higher non-employment risk and hence a riskier income stream. Thus, the agents who have the least access to self-insurance (because they have low assets) in fact have the greatest need for private insurance because their income risk is high. In contrast, at the top of the wealth distribution we find that income risk appears high, but since this is driven by *voluntary* quits to unemployment this is in fact not risk, but rather an optimising decision. The decline in income from the quit is compensated by foregoing the cost of working, and hence the welfare cost of the income risk is dampened relative to simply looking at the income itself. These findings suggest a novel motivation for asset-dependent unemployment insurance (Rendahl, 2012) in order to help low wealth agents search for safer jobs.

Related Literature Our paper contributes to both the empirical and quantitative literature on incomplete market models, as well as richer models of labour market frictions and decisions. Aiyagari-Bewley-Hugget-Imrohoroğlu incomplete market models have been extended to include richer income processes as data and modelling power improve. A large literature extends the income process to be more realistic, for example incorporating richer income data from papers such as Guvenen et al. (2021), but while maintaining that the income process is exogenous. Our focus is instead within the literature that micro-founds the income process in the search tradition.

On the empirical side, a small but growing literature has documented the effect of wealth on labour market transitions and hence the income process. An important finding, repeated across several papers, is that non-employed workers with higher wealth spend longer in unemployment, i.e. have lower EU rates. This is shown by Bloemen and Stancanelli (2001), Algan et al. (2003), Chetty (2008), Herkenhoff et al. (2016), and Griffy (2021), among others. Some of these papers additionally show that a longer time in unemployment is due to higher reservation wages, or higher realised wages or productivity in their new job. Wealthier workers also perform less on the job search, as shown by Lise (2013) and Griffy (2021).

Our focus is on worker transitions *out* of employment, and here there is less empirical evidence. Algan et al. (2003) show that higher wealth individuals have higher quit rates to unemployment, which we also find in the top half of our U-shaped pattern. Rendon (2006) develops a model which can replicate this fact, and hence their model mechanism shares similarities to our own. They additionally show empirically that workers leaving employment is

Figure 1: Labour market status and transitions



typically followed by a fall in wealth, while gaining employment is typically followed by a rise in wealth, which mirrors our finding that workers making EN transitions suffer dramatic and persistent wealth declines. Larkin (2019) documents that workers with higher EU risk have more liquid portfolios. This is in principle not in conflict with our finding that workers with higher EU risk have lower wealth in the left hand side of the U, both due to our flexible empirical specification picking up non-monotone effects and because we focus on total wealth and not portfolio composition. We contribute to these papers by documenting a novel U-shaped pattern, and developing a theory which can address both sides of this pattern.

Many of the above papers additionally develop rich theoretical models that can explain the relationships found in the data. A joint theoretical literature also exists which combines labour market models and incomplete markets. Papers which deal more with the aggregate or business cycle effects of these interactions include Acemoglu and Shimer (1999), Krusell et al. (2010), Ravn and Sterk (2017), den Haan et al. (2018), and Ravn and Sterk (2021). Herkenhoff (2019) and Braxton et al. (2020) study the effect of credit access on non-employed search decisions, and Lentz and Tranæs (2005) look at how wealth can explain duration dependence in UE rates. Eeckhout and Sepahsalari (2021) demonstrate how wealth affects the allocation of workers to jobs of differing productivities, and Huang and Qiu (2021) the mismatch between firm and worker types. Finally, Hubmer (2018) develops a rich job ladder model that includes incomplete markets, and Chaumont and Shi (2022) build a job ladder model with directed search where lower wealth agents have higher job to job transition rates, in line with the data.

The rest of the paper is structured as follows. Section 2 presents the data, and Section 3 our empirical results. Our quantitative model and results are given in Section 4, and in Section 5 we conclude.

2 Data

Our data is taken from the Panel Study of Income Dynamics (PSID), a longitudinal study of households in the United States. The survey ran annually from 1968, interviewing around 9000 families before switching to biannual surveys from 1997 until present. The PSID contains detailed questions on a number of social issues and importantly for our purposes, there is detailed data on labour market status and household wealth.[5] Due to the availability of the wealth data and other continuities in the data such as consistency in the variables that describe individual histories in the labour market, which we use to construct transitions between employment and non-employment, our core estimation sample is limited to 1999-2017. However the waves prior to 1999 are used to construct tenure and transition variables whenever necessary.

We limit our sample to individuals between the ages of 18 and 65 from the core PSID sample dropping those who are from the immigrant sample and the Survey to Economic Opportunity sample. We include only individuals who are consistently the household reference person or spouse whilst in the sample, and include both men and women. We only include individuals once they join the labour market, and only include them until the point they permanently leave the labour market.[6] We further restrict to those who do not experience self employment nor government employment, and are not employed in farming, mining or public administration industries. We also drop observations with a real hourly wage less than 1 dollar. All of those restrictions are standard and have been employed in earlier work. Given our interest in transitions out of employment, we further require that we observe an individual for at least two consecutive waves of the survey after implementing all the other sample restrictions. We end up with a panel containing 27,832 observations on 5,151 individuals. We have on average 5.4 observation per individual in the data.

Our main dependent variable is whether an individual has made *at least one* transition from employment to non-employment between survey waves. To measure whether a worker has transitioned between employment and non-employment between consecutive waves in years t and $t+2$ we use information from both waves, and create a binary variable $EN_{i,t}$. To be recorded as having made an EN transition ($EN_{i,t} = 1$), the worker must satisfy the following conditions. Firstly, the worker should report being in employment (E) in wave t. Next, we check the worker's labour market status in year $t+2$. If they report being either unemployed (U) or inactive (I), we set $EN_{i,t} = 1$. If, however, they report being employed in year $t+2$ and the information on their tenure suggests they switched employers between interviews, we look into questions asking they spent any time in unemployment or inactivity between years t and $t+2$. If the workers report a spell of non-employment, we set $EN_{i,t} = 1$ as well. Otherwise, we set $EN_{i,t} = 0$.

Therefore, there are three distinct types of transitions out of employment in year t which are induced by reported labour market histories that we lump into our $EN_{i,t}$ variable: to unemployment, *EU*, to inactivity, *EI*, and to employment with an intermittent spell of non-employment, *E(N)E*. We illustrate this procedure on Figure 1.

[5] Many other papers relied on PSID data and used information on wealth and/or labour market transitions from this survey. A non-exhaustive list includes Kambourov and Manovskii (2009), Kaplan, Violante, and Weidner (2014), Cortes (2016) and Griffy (2021).

[6] For example, an individual who was a student when they joined the survey would not be included in our sample until they become active in the labour market reporting either being employed or unemployed. We assume a worker permanently abandons the labour market if they do not report being either employment or unemployment from a given wave onwards.

Table 1: Labour Market Status and Flows

	Mean		Mean
Labour Market: Status and Flows		**Type of EN transition**	
Unemployed	0.051	EU	0.039
Inactive	0.039	EI	0.021
EN	0.140	E(N)E	0.079

Note: The sample contains 27,832 observations on 5,151 individuals. The sample includes individuals aged 18 to 65, who are only added to the sample once they join the labour market. They are then dropped from the sample once they leave the labour market and they do not appear again as employed. We restrict our sample to the core PSID sample who are not self-employed or working for the government or in farming related occupations. Lastly, our sample includes individuals which we observe for at least two consecutive waves.

We present the summary of labour market status and flows in our sample in Table 1. Approximately 9% of the sample is in non-employment at the interview date. A quarter of workers will make a transition out of current-wave employment and a bit more than half of those are EN transitions. The majority of EN transitions are of the $E(N)E$ type.[7]

The key independent variable will be the position of the household in the wealth distribution. To measure this, we use two wealth variables from the survey, *Net Wealth without Home Equity* and *Net Wealth with Home Equity*. These are calculated and reported in the survey based on more detailed questions about assets and liabilities at the household level. Home equity is harder to tap into than, say, cash or stocks, therefore the first wealth variable proxies for the liquid part of net wealth. As mentioned earlier, we are keeping the household heads and their spouses, if present, in the sample. While this increases the explanatory power of the data, it also induces a complication in comparing household wealth between singles and couples. To address that, we assume an equal split of household wealth between couples.[8] We present descriptive statistics of the net wealth variables in Table 2. Both measures of net wealth and their growth feature strong right-skew and large dispersion.

We are also interested in a standard set of demographic characteristics to be used as additional controls in our regressions. To this end, we keep information on gender, age, marital status, number of children, ethnicity, and educational attainment in the data. Furthermore, we also include industry and occupation controls, where these are measured using aggregated census industry and occupation codes to the 2 digit level. Last, but not least, we collect information on hourly wage at the main job at time of interview. We report descriptive statistics of our sample in Table A.1. All monetary variables are expressed in 2015 US dollars.

[7] We discuss further details of the construction of the $EN_{i,t}$ variable and robustness of our main result to an alternative approach in Online Appendix B.1.1.

[8] One can imagine ranking individuals in the sample differently, e.g., based on the distribution of household wealth or constraining the sample only to household heads. We offer more discussion of this and robustness checks in the Online Appendix B.1.2 and B.1.3, respectively.

Table 2: Distribution of Per-Capita Net Wealth and its Accumulation

Net Wealth	1-st Quartile	Median	3-rd Quartile	Mean	Std. Dev.
with Home Equity					
Level	3.19	25.02	86.88	88.05	259.23
2-year growth	-6.24	8.86	45.03	37.06	263.02
4-year growth	-3.10	19.87	76.08	70.20	294.91
6-year growth	0.51	33.87	106.97	103.21	322.56
without Home Equity					
Level	0.81	9.39	40.37	55.89	229.01
2-year growth	-7.35	2.89	23.39	24.62	249.34
4-year growth	-6.15	6.74	42.62	48.21	273.30
6-year growth	-4.44	10.62	63.77	71.35	297.96

Note: All values expressed in thousands of 2015 US dollars. The sample contains 27,832 observations on 5,151 individuals. The sample includes individuals aged 18 to 65, who are only added to the sample once they join the labour market. They are then dropped from the sample once they leave the labour market and they do not appear again as employed. We restrict our sample to the core PSID sample who are not self-employed or working for the government or in farming related occupations. Lastly, our sample includes individuals which we observe for at least two consecutive waves.

3 Empirical Results

In this section, we empirically investigate the relationship between wealth and EN transitions using the PSID data. We find that this relationship is U-shaped and is robust to a battery of checks. Then, we document that EN transitions have sizeably negative, persistent, and statistically significant effects on wealth accumulation.

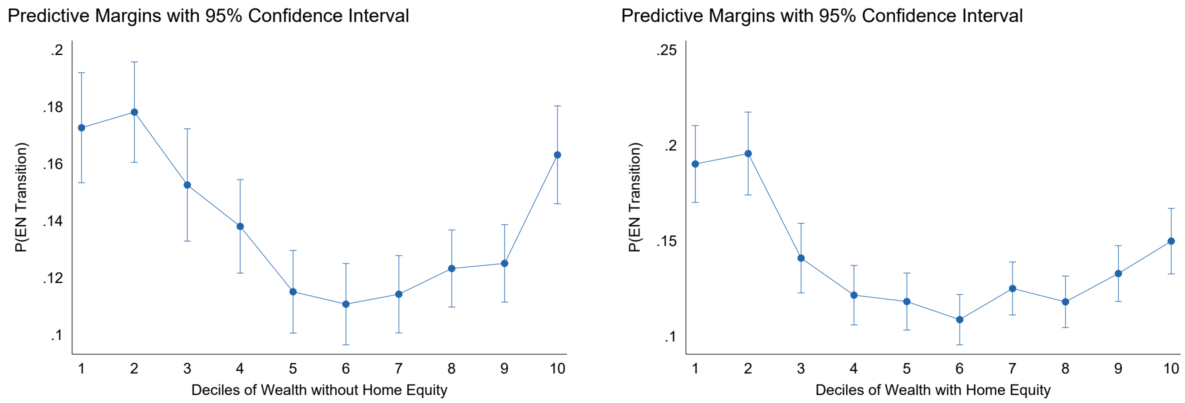
3.1 Estimation Strategy

Our starting point is the following linear probability (LPM) model specification:

$$Pr(EN_{i,t}|Wealth_{i,t}, \mathbf{X}_{i,t}) = \alpha + \sum_{t=1}^{T} \delta_t + \sum_{d=1}^{D} \delta_d W_{i,t}^d + \mathbf{X}_{i,t}'\boldsymbol{\beta} + \varepsilon_{i,t}. \tag{1}$$

This regression estimates the determinants of the probability of observing an EN switch for individual, i between time t and $t+2$, coded as the binary variable $EN_{i,t}$. We partition the wealth distribution into D ranked bins, $d \in \{1, ..., D\}$ and the main variable of interest is the time-t per-capita wealth, $Wealth_{i,t}$, where we use either liquid or total net wealth. We employ indicator functions equal to one if $Wealth_{i,t}$ belongs to bin d of the wealth distribution which we denote $W_{i,t}^d$. The coefficients δ_d capture the effect of belonging to wealth bin d on the probability of making an EN switch. As our sample spans both booms and busts, we control for business cycle fluctuations with time dummies δ_t. We include additional controls in the regression in order to control for standard observables. This is important for identifying the true effect of wealth on EN transition, as wealth might be correlated with other observables, such as wages or age, which also affect the probability of making such a transition. Other controls

Figure 2: Margins of Deciles of wealth on the probability of an EN-transition (LPM).



(a) Liquid Net Wealth

(b) Total Net Wealth

Note: These figures plot the predictive margins on deciles of wealth from a linear probability model regression as presented in equation 1. Panel 2a includes deciles of wealth without home equity, whilst Panel 2b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

are summarised in $\boldsymbol{X}_{i,t}$, with vector of $\boldsymbol{X}$ controls for individual i in time t. The additional covariates include: gender, race, years of completed schooling, whether the individual is married, and their number of children. We further control for a cubic polynomial of age, region, and for log hourly wage. Standard errors are clustered at the individual level.[9]

3.2 EN Transitions as a Function of Wealth

To begin with, we estimate (1) splitting the wealth distribution into deciles. We then plot the marginal effects of being in a given wealth decile in Figure 2. Panel (a) represents the results using liquid wealth, and Panel (b) is for total wealth. Regardless of the measure of wealth used, we observe a rough U-shape in the probability of an EN transition, with the workers in the top 10% of the household wealth distribution having a higher likelihood of an EN transition than those in the median-to-90-th-percentile part of the distribution. Lower wealth individuals, particularly those in the bottom two deciles, also have a higher likelihood of experiencing an EN transition. Indeed, those workers actually have the highest EN rates across both measures of wealth. This U-shaped relationship is, to the best of our knowledge, novel, and represents the key empirical contribution of our paper.[10]

The figures give 95% confidence bands, showing that the results are quite precisely estimated and suggesting statistically significantly different EN rates across the wealth distribution. The results are also quantitatively significant. Workers in the middle of the wealth distribution typically have a 12% probability of reporting an EN transition in the two years between sample waves. For workers in the bottom wealth decile this is closer to 17%, meaning

[9]The estimated coefficients for the LPM specification are qualitatively and quantitatively similar to the marginal treatment effects obtained from logit and probit regressions, see Online Appendix B.1.4.

[10]We show that the relationship between wealth and EN transitions is substantially different from how wealth impacts on transitions from employment to employment and from non-employment to employment in Online Appendix B.2.

Table 3: Focusing on the Tails of the Wealth Distribution.

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Low Wealth	0.054***	0.039***	0.040***	0.085***	0.056***	0.056***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
High Wealth	-0.043***	0.040***	0.037***	-0.053***	0.029***	0.025***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Observations	20604	19128	19051	20604	19128	19051
Individuals	5008	4835	4830	5008	4835	4830
R^2	0.006	0.063	0.070	0.010	0.064	0.070
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes
Industry/Occupation	No	No	Yes	No	No	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

a bit less than 50% increase in their *EN* rate. Similarly, for workers in the top wealth decile their *EN* rates is around 14-15% depending on the measure of wealth used, therefore being at least 20% higher than for workers in the middle of the wealth distribution.

Secondly, to perform a sharp test of the statistical differences across wealth distributions, and to allow easy comparison of results across specifications and motivated by evidence reported in Figure 2, we split the wealth distribution into three bins, the bottom 10%, middle 80% and top 10%. For the remainder of the paper we therefore focus on the following specialised version of equation (1):

$$Pr(EN_{i,t}|Wealth_{i,t}, \mathbf{X}_{i,t}) = \alpha + \delta_1 W^1_{i,t} + \delta_{10} W^{10}_{i,t} + \mathbf{X}'_{i,t}\boldsymbol{\beta} + \sum_{t=1}^{T} \delta_t + \varepsilon_{i,t}. \tag{2}$$

The dummies δ_1 and δ_{10} capture the relative difference in the propensity to experience an *EN* transition by workers in the tails of the wealth distribution relative to the middle group. Finding that both δ_1 and δ_{10} are statistically significantly greater than zero will therefore constitute evidence in favour of the U-shaped pattern. We refer to these dummies as *Low Wealth* and *High Wealth* from now on.[11]

[11] Alternatively, one could specify the dummies differently. In particular, Figure 2 suggests that the *Low Wealth* dummy could be defined to include bottom two deciles of the wealth distribution. We explore this possibility in Online Appendix B.1.5.

Table 4: *EN* Transitions and Wealth Accumulation

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	t+2	t+4	t+6	t+2	t+4	t+6
EN Transition	-1.239***	-1.037*	-3.913***	-2.186***	-3.005***	-10.272***
	(0.288)	(0.606)	(1.251)	(0.482)	(1.057)	(2.605)
Observations	14765	8344	4112	14765	8344	4112
Pseudo-R^2	0.009	0.019	0.030	0.027	0.049	0.063
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Occupation	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Robust standard errors. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

We present the results of estimating Equation (2) in Table 3 which shows the estimated coefficients for *Low Wealth* and *High Wealth* across both wealth measures and considering various combinations of controls. The results are fairly similar for liquid and total wealth, and so we focus on liquid wealth in columns 1 to 3, with results for total wealth given in columns 4 - 6.

For liquid wealth, our preferred specification is in column 3, which includes both individual controls and controls for the industry and occupation of the individual's current job. We find a statistically and economically significant U-shape in the *EN*-wealth relationship. Both the bottom and top 10% of the wealth distribution have similarly higher probabilities of an *EN*-switch compared to the middle of the distribution: by 4 p.p. and 3.7 p.p. higher, respectively. These estimates agree closely with the differences in *EN* rates across the whole wealth distribution shown in Figure 2. In columns 2 and 1 we gradually remove controls to identify the biases that would be introduced if they had been excluded. Column 2 shows that the results are very similar excluding the industry and occupation controls, suggesting that the driving force of the U shape pattern are not the high-level characteristics of the individual's work which could be correlated with their industry and occupation.

In column 1 we do not consider any additional controls apart from year fixed effects, so these numbers simply reflect the correlations between wealth and probability of an *EN* switch controlling for business cycle fluctuations. Strikingly, we do not observe the U-shape in propensity to switch, and instead find a purely downwards sloping relationship. Thus the fact that low wealth agents are more likely to make *EN* switches is visible even when excluding controls, with the coefficient shrinking, but remaining economically large, when including controls. On the other hand, the right side of the U shape — the fact that the workers in the top wealth decile are also more likely to switch — is only visible when including controls, as the coefficient goes from negative to positive between columns 1 and 3. This is likely because wealth is positively correlated with variables such as wage and age which might predict a lower probability of making an *EN* switch.

3.3 Consequences of *EN* Transitions

Next, we look at the consequences of *EN* transitions for wealth accumulation. We estimate Equation (3) where the dependent variable is the change in individual net wealth k years from current interview date (in thousands of US dollars in 2015). Apart from using the full set of controls we also add the $EN_{i,t}$ dummy. To avoid the effects of extreme outliers present in the data, we estimate a quantile regression, taking the median as the targeted moment.

$$W_{i,t+k} - W_{i,t} = \alpha + \mathbf{X}'_{i,t}\boldsymbol{\beta} + \sum_{t=1}^{T} \delta_t + \mathbb{1}_{EN_{i,t}} + \varepsilon_{i,t} \tag{3}$$

The main result of this exercise, which we report in Table 4, is that there are persistent, significant and negative effects of *EN* transitions on growth of per-capita wealth. Relating the estimated coefficients from Table 4 to median per-capita wealth accumulation in Table 2, we find that the immediate effect of *EN* is a bit less than a half of median net wealth growth in 2 year time. This effect then shrinks slightly to approximately 40% over six years. As far as net wealth with home equity is concerned, the immediate effect is approximately one quarter of median wealth accumulation which then increases mildly to about 30% over six years.

3.4 Robustness Checks

We have subjected our novel result on the U-shaped relationship between *EN* transitions and net per-capita wealth to a battery of tests. We provide details of their results in the Appendices and give a brief overview here.

Firstly, we test if our result is driven by composition effects that are specific to demographic characteristics of primary importance: gender (e.g., because of women being more risk averse than men), family composition (e.g., couples and singles search behaviour differing) and education (e.g., because of inherent differences in riskiness of jobs specific to education). Results presented in Table A.2 demonstrate that this is not the case. The point estimates of *Low Wealth* and *High Wealth* coefficients are positive and significant in all but one specification.

Secondly, we investigate the robustness of our result to life-cycle effects. Again, our result is robust, see Table A.3, which demonstrates that the U-shape prevails well into mid-age. That the U-shape is present among the youngest workers emphasizes that our results are not driven via spurious correlations from other variables correlated with wealth. The wealth observed for younger individuals is more likely to be family wealth, rather than wealth they have personally accumulated over time from employment. Hence, the finding that wealth affects *EN* transitions for younger people is even less likely to be by correlations between wealth and other variables such as wages or unobserved differences in *EN* risk.

Thirdly, we also checked for potential reverse causality. One could argue that particularly the left side of the U-shape could be due to some workers being permanently exposed to higher non-employment risk which would then impede their accumulation of wealth. In that case, non-employment would cause low wealth, not the other way round. As can be seen in Table A.4, this is not the case.

4 Quantitative Model

In the remainder of the paper we present a heterogeneous agent model of incomplete markets with a frictional labour market where workers face heterogeneous separation risks. The model builds on the incomplete markets models of Bewley (1983), Imrohoroğlu (1989), Huggett (1993), and Aiyagari (1994).

4.1 Description of the model

The model is in continuous time, and is populated by a unit mass continuum of ex-ante identical workers. We focus purely on the worker side of the market, making this a partial equilibrium model where the distribution of job opportunities is exogenous. We suppress the time index, t, and worker index, $i \in [0,1]$, where it does not cause confusion.

Workers are infinitely lived and discount future at rate $\rho > 0$. They are risk averse, with preferences over the consumption flow, c_t, described by a utility function $u(c_t)$ with $u'(c_t) > 0$, $u''(c_t) < 0$. Workers can be either employed or non-employed (inactive), where we discuss the distinction between unemployment and inactivity below. Working entails a fixed utility cost $f > 0$, which is not incurred when non-employed.

Workers can borrow and save only using a risk free bond with interest rate r. We denote a worker's assets with a_t and impose the borrowing constraint $a_t \geq \underline{a}$. Given current income y_t, which can be either wages or non-employment income, assets evolve according to

$$\dot{a}_t = y_t + ra_t - c_t \tag{4}$$

Since the consumption flow must be finite, assets will never jump in this model ($-\infty < \dot{a} < \infty$). This means that the borrowing constraint $a_t \geq \underline{a}$ will never become binding in the next instant of time whenever $a_t > \underline{a}$. Therefore, the borrowing constraint only places constraints on decision making when $a_t = \underline{a}$, at which point consumption must satisfy $\dot{a}_t \geq 0 \implies c_t \leq y_t + r\underline{a}$. The fear of hitting this borrowing constraint means that lower wealth agents become effectively more risk averse.

When non-employed, workers receive benefits b as income. This could alternatively be interpreted as home production. This is received regardless of whether a worker actively searches for a job or not, and so we do not distinguish between unemployment and inactivity in the model, for example by assuming that the government cannot observe search effort. While non-employed, workers search for a job. All jobs pay the same constant wage, w, where we abstract from wage differences because our empirical work identified that all of our findings held even controlling for wages. We thus consider our model as distinguishing the behaviour of different workers within the same broad wage level (for example, within a group with the same educational attainment) but with different levels of assets due to their idiosyncratic employment histories.

There are two types of jobs in the economy, distinguished by their level of risk. "Risky" jobs are destroyed, returning the worker to unemployment, at rate δ_h. "Safe" jobs are destroyed at the lower rate $\delta_l < \delta_h$. We abstract from on the job search, and so only non-employed workers search for jobs.[12] We assume that the risky job is easier to find than the safe job, which motivates why workers might search for the risky job despite it being otherwise dominated by the safe job. As we will discuss, this assumption is also consistent with the existing evidence (e.g. Herkenhoff et al., 2016) that job finding rates are higher for low wealth workers.

Specifically, we assume that non-employed workers must direct their search to either the risky or safe job at any given moment in time. Search is costless and search effort is fixed. If an non-employed worker chooses to search for a risky job, they will receive a job offer at rate $\lambda(\delta_h)$. If they choose to search for a safe job it will arrive at the slower rate $\lambda(\delta_l) < \lambda(\delta_h)$. If an non-employed worker would prefer to remain non-employed because the value of unemployment dominates the value of both jobs, they may also choose not to search for a job. Similarly, if an employed worker would prefer to be non-employed and quit, we allow them to do so.

4.2 Worker value and policy functions

The above model structure implies the following value functions for workers, expressed as Hamilton-Jacobi-Bellman equations. Define $v^u(a)$ as the value of being non-employed with current wealth a. This is given by:

$$\rho v^u(a) = \max_{c \geq 0, \delta \in \{\delta_l, \delta_h\}} u(c) + v^u_a(a)\,(b - c + ra) + \lambda(\delta)(\max\{v^e(a,\delta), v^u(a)\} - v^u(a)) \tag{5}$$

subject to $c \leq b + r\underline{a}$ when $a = \underline{a}$. The first and second terms on the right hand side describe the utility from consumption and the drift in value from the implied change in assets. The final term describes the change in value if a worker becomes employed, given the risk δ of the job they search for and its arrival rate $\lambda(\delta)$.

Define $v^e(a,\delta)$ as the value of being employed with assets a at a job with risk δ. This is given by:

$$\begin{aligned}\rho v^e(a,\delta) = \max_c u(c) - f + v^e_a(a,\delta)\,(w - c + ra) + \delta(v^u(a) - v^e(a,\delta)) + \\ + \zeta(\max\{v^e(a,\delta), v^u(a)\} - v^e(a,\delta))\end{aligned} \tag{6}$$

Relative to an non-employed worker, notice that an employed worker pays the utility flow cost f, and has income w. The term $\delta(v^u(a) - v^e(a,\delta))$ captures the probability of a layoff and returning to unemployment. Finally, to allow workers to quit from employment in a tractable way, we assume that workers may not instantaneously quit, but receive the opportunity to quit at rate ζ. If $v^e(a,\delta) < v^u(a)$, they will then do so, and transition to unemployment. We

[12]Given that we abstract from wage differences, on the job search in our model would only be between levels of risk, with workers in high risk jobs searching to move up the safety ladder to a low risk job. While this is an interesting feature, in the data job-to-job moves are also driven by workers moving to higher wage jobs, and so calibrating a realistic degree (e.g. 2% monthly rate) of on the job search in a model without wage differences would overstate the degree to which workers perform on the job to move up the safety ladder.

interpret this rate as the fact that workers must give notice before quitting, for example having to work for a final month.[13]

The solution to the consumption-saving problem for all workers is standard. For employed workers with $a > \underline{a}$ the first order condition gives $u'(c) = v^e_a$, and similarly so for non-employed agents. Workers with $a = \underline{a}$ may be constrained to set a lower value of consumption by the borrowing constraint. More important for our analysis are the worker's labour market decisions, which we discuss in more detail along with our results. In brief, we will find that low wealth non-employed workers will search for risky jobs, and high wealth employed workers will choose to quit to non-employment, both of which are important for matching the U-shape in the data.

4.3 Illustrative Calibration

We calibrate our model to match standard labour market facts, as well as our new empirical results. The calibration is monthly, so that one unit of time equals one month. We set the discount rate ρ to give a 5% yearly rate, and the risk free rate r to a 2% yearly rate.

We normalise the wage to $w = 1$ and set $b = 0.4$ to give a 40% replacement rate. We specialise to a CRRA utility function $u(c) = c^{1-\sigma}/(1-\sigma)$ and set a relatively high value of risk aversion of $\sigma = 4$. We set the borrowing constraint to $\underline{a} = -w$ to allow borrowing of up to one month's wage. We set the notice period for employed workers to quit to $\zeta = 1$, so that workers receive the opportunity to quit once a month on average, in line with a one month notice period.

Moving on to the labour market moments, we set the parameters of the safe job to match standard labour market moments. We compute the EN rate in the model by averaging across all EN transitions from safe jobs, risky jobs, and quits to unemployment, and match an average monthly EN rate of 3%. We target this number by adjusting the separation rate in the safe job, δ_l. We target a 6% unemployment rate, which we achieve by adjusting the job finding rate of the safe job, $\lambda(\delta_l)$.

We set the parameters of the risky job and the cost of working to match our new fact that the EN-wealth relationship is U-shaped. The results in Figure 2(a) show that the ratio of the EN rate in the bottom decile (0-10%) of the wealth distribution to the rate in the fifth decile (40-50%) of the distribution is roughly $0.14/0.09 = 1.56$. Since low wealth workers will search for the risky job in equilibrium, we choose δ_h to match this same fact in our model, by raising the separation rate of the risky job. We set the arrival rate of the risky job, $\lambda(\delta_h)$ to match the ratio of the EN rate in the third decile to that in the fifth decile, which is roughly $0.12/0.09 = 1.33$ in the data. By controlling the relative attractiveness of searching for the risky job, this controls at which wealth level wealth-poor agents will flip from searching for the risky job to searching for the safe job, and hence how far up the wealth distribution high EN risk remains elevated.

[13] This structure is computationally helpful, as it allows us to model notice periods in a recursive way. Additionally, by ruling out that workers can instantaneously quit, we avoid having to specify the problem as a Linear Complementarity Problem, allowing us to use fast, standard methods to solve the value function. As $\zeta \to \infty$ the solution approaches the solution where workers can instantly quit, and in practice the results are very similar even with $\zeta = 1$.

Table 5: Quantitative Model: Calibration

Parameter	Description	Value	Source/Target
		Predetermined	
w	Wage	1	Normalisation
b	UI Benefits	0.4	40% Replacement Rate
σ	Risk Aversion	4	–
ρ	Discount Factor	0.0043	5% Annual
r	Real Interest Rate	0.0017	2% Annual
ζ	Avg. Termination Notice	1	1 Month
$\underline{a}$	Borrowing constraint	-1	1 Month's Wages
		Internally calibrated	
δ_l	Safe Jobs EN Rate	0.0194	3% Monthly EN Rate
δ_h	Risky Jobs EN Rate	0.0411	$\frac{\text{EN in decile 1}}{\text{EN in decile 5\%}} = 1.56$
$\lambda(\delta_l)$	Safe Jobs Arrival Rate	0.3785	6% Non-employment Rate
$\lambda(\delta_h)$	Risky Jobs Arrival Rate	0.5498	$\frac{\text{EN in decile 3}}{\text{EN in decile 5}} = 1.33$
f	Disutility of Work	0.6462	$\frac{\text{EN in decile 10}}{\text{EN in decile 5}} = 1.44$

Note: Parameter values and target moments. See the text for details of our calibration strategy.

Similarly, the results in Figure 2(a) show that the ratio of the EN rate in the top decile of the wealth distribution to the rate in the fifth decile of the distribution is roughly $0.13/0.09 = 1.44$. Since high wealth individuals will quit to unemployment, driving a high EN rate via quits, we choose f to match this same fact in our model, by changing the utility cost of working. We calculate both of these ratios using the monthly separation rates at each wealth decile in our model.

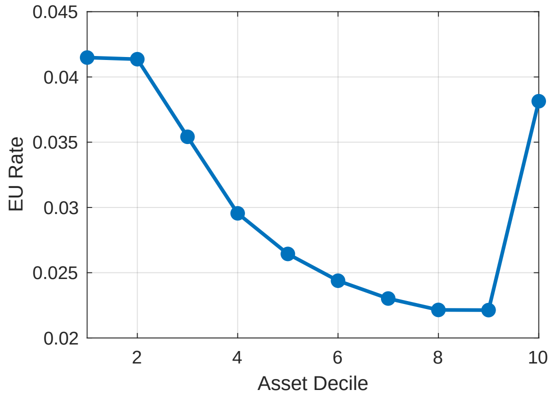
Discussion of identified parameter values Our target moments and identified parameter values are given in Table 5. The estimation finds that reasonable values for these parameters are required to hit the moments. The safe job has a separation rate of 1.9% per month, and a job offer arrival rate of 38% per month. The risky job has a separation rate nearly two times higher, at 4.1% per month, but a faster job offer arrival rate of 55%. This implies an average wait time of 2.6 months for a safe job and only 1.8 months for a risky job.

Finally, the disutility of work parameter can be interpreted as follows. The hypothetical flow utility gap between consuming the wage w and benefits b is $u(w) - u(b) = 4.875$. So the flow disutility of working $f = 0.6462$ is equal to 13% of this consumption value. We thus identify a relatively small cost of working, which is sufficient to drive quits towards the top end of the wealth distribution.

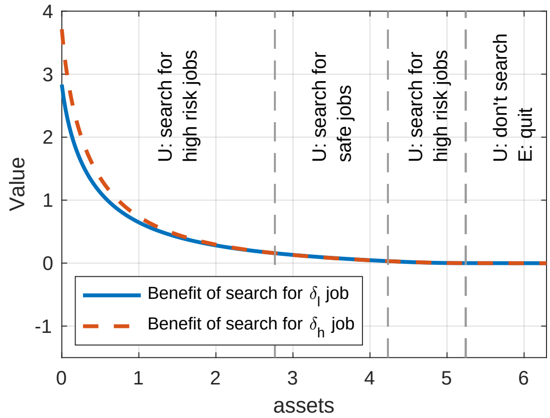
4.4 Result 1: "U shaped" EN-wealth relationship

The first result from our quantitative model is that we are able to successfully reproduce the U shaped EN-wealth relationship that we found in the data. This is shown in Figure 3(a), where we plot the EN rate by wealth decile in our estimated model. We replicate well the data from Figure 2, in particular: i) the U shaped pattern, ii) the relative EN rates at the top and bottom 10% of the distribution, and iii) the gradual reduction in EN rates by wealth as wealth increases

Figure 3: EU Rate and Polcy: Model



(a) EN by wealth decile



(b) Search and quit Policies

The left figure gives the average *EN* rate for employed workers by wealth decile. We calculate the wealth distribution across all workers in the ergodic distribution, and the *EN* rate is calculated as the monthly rate. The right panel plots the benefit of searching for each job type at each wealth level, as defined in the text. The horizontal lines denote wealth levels where the optimal job to search for switches.

from low levels, and the increase in EN rates only at the top decile. While these moments are targeted, it should be noted that there is nothing mechanical in the model that generates these patterns: as we shall we, it is the endogenous decisions of workers which drive them.

We start by explaining the left side of the U, or why EN rates are elevated for low wealth workers. Consider whether an non-employed worker would prefer to search for a risky or safe job. Inspecting (6) shows that they will prefer to search for the risky job if:

$$\lambda(\delta_h)(v^e(a,\delta_h) - v^u(a)) > \lambda(\delta_l)(v^e(a,\delta_l) - v^u(a)), \tag{7}$$

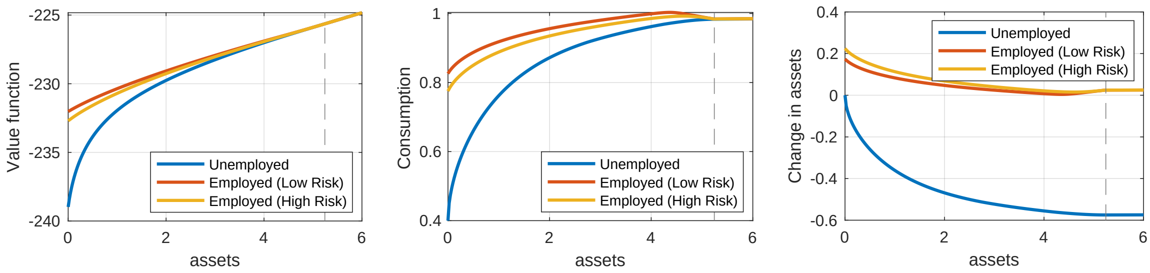
which can be expressed as:

$$\frac{\lambda(\delta_h)}{\lambda(\delta_l)} > \frac{v^e(a,\delta_l) - v^u(a)}{v^e(a,\delta_h) - v^u(a)}. \tag{8}$$

That is, a worker will choose to search for the risky job if the increase in the speed of receiving a job offer ($\lambda(\delta_h)/\lambda(\delta_l) > 1$) compensates for the fact that the higher risk job gives relatively lower value ($(v^e(a,\delta_l) - v^u(a))/(v^e(a,\delta_h) - v^u(a)) > 1$ since $v^e(a,\delta_h) < v^e(a,\delta_l)$). Without further information, it is not possible to say which side is greater and hence which job is preferred. Indeed, non-employed workers with different asset levels will prefer to search for different jobs. In Figure 3(b) we plot $\lambda(\delta_h)(v^e(a,\delta_h) - v^u(a))$ and $\lambda(\delta_l)(v^e(a,\delta_l) - v^u(a))$ which we use to show which job workers prefer searching for at each range of the wealth distribution.

Intuitively, non-employed workers with low wealth are very effectively risk averse, because they know they will run out of wealth soon. They thus will choose to search for the risky job, which is quicker to get. Mathematically, this is represented by the fact that $v^u(a)$ becomes very concave in a for low values of a. Since $v^e(a,\delta_h) - v^u(a)$ is smaller than $v^e(a,\delta_l) - v^u(a)$, the steep decline in $v^u(a)$ as a falls leads to a proportionally larger increase in the denominator, causing the right hand side fraction to fall and pushing agents towards choosing the risky

Figure 4: Value and Policy Functions



(a) Value Function (b) Consumption (c) Asset change ($\dot{a}$)

Figures give the value and policy functions in the model across asset levels. The blue, red, and yellow lines in panel (a) give the value functions $v^u(a)$, $v^e(a, \delta_l)$, and $v^e(a, \delta_h)$ respectively, and similarly for the consumption and $\dot{a}$ policy functions in panels (b) and (c).

job.[14] This can be seen in panels (a) and (b) of Figure 4, where consumption and value fall very fast for non-employed workers at low wealth levels. This leads low wealth workers to search for the risky job before switching to searching for the safe job for intermediate wealth levels, as shown in Figure 3(b).

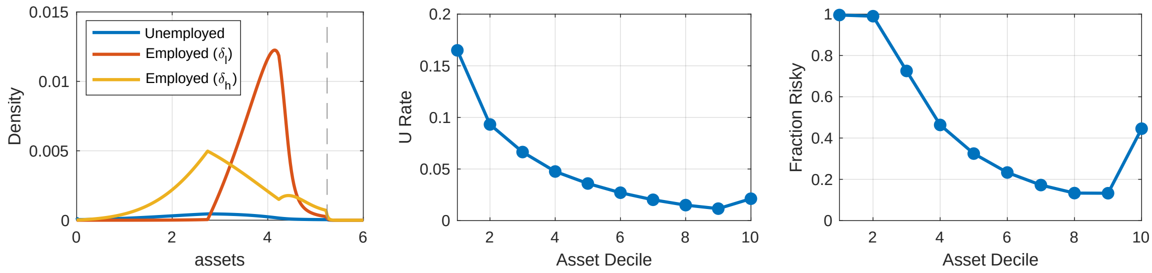
Surprisingly, despite saving them only three weeks of expected time in non-employment, low-wealth workers prefer to search for the risky job, because the consumption drop from being non-employed at low-wealth is so severe. Notice that this means that our model is also endogenously consistent with the existing evidence that low wealth agents have higher UE rates, as discussed in the literature review. This justifies our assumption that risky jobs have higher arrival rates, because the fact that low wealth agents search for these jobs then drives their higher UE rates. The calibrated differences in the arrival rates of the two jobs also appear in line with estimates of the sensitivity of UE rates to wealth and credit.[15] Finally, recall that we compute the EN-wealth relationship by looking at current wealth, not wealth at the time a job was taken (as in our empirical work). Since wealth is a persistent state variable the realised EN rate becomes correlated with current wealth.

Moving on to the right hand side of the U, this is driven by quits in our model, consistent with the suggestive evidence that quits are also more important at high wealth in the data. Sufficiently wealthy workers quit to unemployment because working is costly, due to the fixed cost f, and they can afford to finance high consumption in non-employment by running down their savings. Figure 3(b) shows that workers only quit employment for the highest wealth levels, above a certain threshold. At this high level of wealth, the drop in consumption from being non-employed is actually relatively small, as shown in Figure 4(b). Workers who quit therefore run down their savings in a temporary non-employment spell and begin searching for a new job as their savings deplete. An interesting side effect of this is that sufficiently wealthy workers actually start searching for the risky job again above a certain threshold. This

[14] Since a also affects $v^e(a, \delta_h)$ and $v^e(a, \delta_l)$ proving this analytically is challenging. Our numerical results confirm that this intuition holds at our estimated parameter values.

[15] For example, Herkenhoff et al. (2016) show that an increase in credit limits of 10% of prior earnings encourages workers to spend 0.15 to 3 weeks longer in unemployment. While the nature of the experiment differs, the order of magnitude of the difference in UE rates is the same as the difference between the two rates in our model.

Figure 5: Model Distributions



(a) Asset distribution (b) Unemployment rate (c) Risky Employed Fraction

Panel (a) plots the equilibrium wealth distribution across non-employed and employed workers, with the combined sum of the area under the three lines summing to one. Panel (b) gives the unemployment rate at each wealth decile, defined as the fraction of workers in that wealth decile who are non-employed. Panel (c) gives the fraction of employed workers within each wealth decile who are employed in the risky job.

is because they anticipate quitting soon anyway, so are happy to search for the risky job, which they intend to quit anyway, and benefit from the increased NE rate.

4.5 Result 2: Effect of EN switch on future wealth

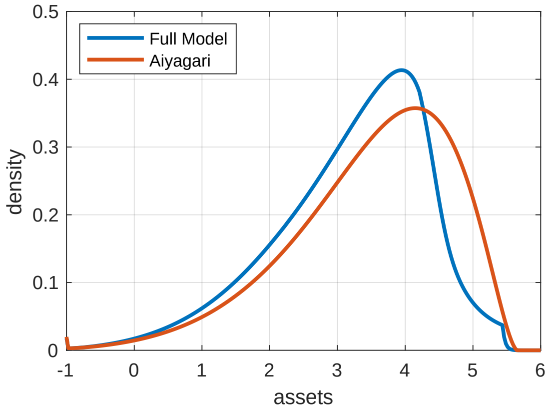
In Section 3.3 we showed that making an EN switch leads to a significant and long lasting decline in future wealth in the data. Intuitively, workers are forced to run down their savings after losing their job in order to finance their consumption without a job. Our model naturally generates this fact, as shown in Figure 4(c). We see that the optimal asset accumulation policy has $\dot{a} < 0$ for non-employed agents at all wealth levels. After losing their job, workers run down their assets gradually in order to sustain consumption while only receiving benefits, and gradually reduce their consumption as their assets fall. Eventually, if they are unlucky enough to remain non-employed for long enough they will deplete their assets all the way to the borrowing limit $\underline{a}$.

Thus, the model generates a feedback loop between wealth and non-employment risk, as in the data: Low wealth leads workers to select into higher unemployment risk jobs, but losing these jobs then leads to lower wealth, and so on. This is a market failure in the model due to incomplete insurance markets: agents would like to be able to insure away idiosyncratic unemployment risk, but cannot. This leads to inefficient consumption and wealth inequality and hence losses in welfare.

Figure 4(c) also shows that employed agents have $\dot{a} > 0$ and so accumulate assets for two reasons. Firstly, they accumulate assets as precautionary savings against becoming non-employed via the involuntary separation shock. Since unemployment risk is higher in the risky job, workers have higher $\dot{a}$ at each wealth level in the risky job than the safe job. Secondly, workers accumulate assets in order to finance their voluntary quits to unemployment, so they can spend some time not paying the cost of working. Since agents in our model are infinitely lived they thus follow cycles of asset accumulation and depletion: In unemployment they run down their assets, and while employed they build them up again.

Notice that this process is doubly painful for low wealth agents, whose consumption is depressed for two reasons. Firstly, their consumption is depressed each time they become

Figure 6: Distributions: Full model vs. Aiyagari-type model



Panel (a) plots the equilibrium wealth distribution across non-employed and employed workers, with the combined sum of the area under the three lines summing to one. Panel (b) gives the unemployment rate at each wealth decile, defined as the fraction of workers in that wealth decile who are non-employed. Panel (c) gives the fraction of employed workers within each wealth decile who are employed in the risky job.

non-employed. Secondly, they select into risky jobs and must therefoe keep their consumption lower than those in safe jobs in order to finance precautionary savings against future job loss.

Finally, in Figure 5 we plot the equilibrium asset distribution in the model, as well as the unemployment rate and fraction of employed workers in risky jobs at each wealth decile.

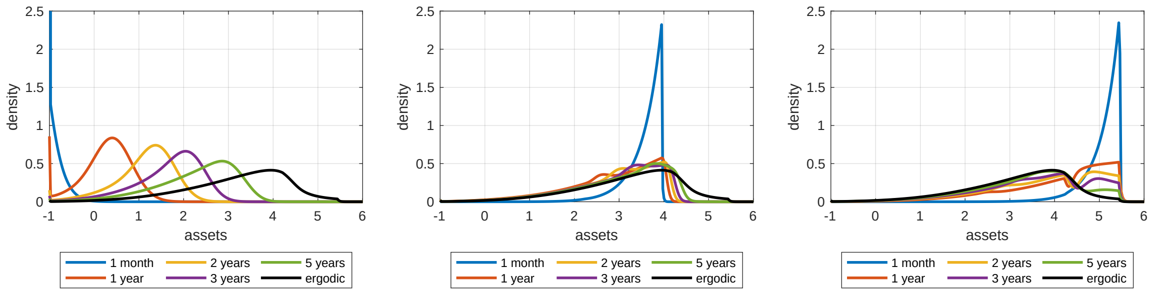
4.6 Result 3: Implications of Endogenous Risk for Distribution of Wealth

We will now show that the structure of risk and its correlation with wealth matter for precautionary savings models. To do this, we solve a pure Aiyagari version of our model with two exogenous income states w and b with transition matrix given by the same overall average EN and NE rates as in our model. The disutility of work f is set to zero and there is no job-risk choice by construction. We keep all other parameters e.g., risk aversion σ and the interest rate r, unchanged. This *benchmark Aiyagari* model has the same observable EN and NE rates. However, there are significant differences between the two models in incentives to accumulate wealth, wealth distribution, and the importance of the precautionary savings motive.

To show this, we plot the wealth distribution in our model and the Aiyagari model in Figure 6. Since the interest rate has not been adjusted and the incentives to accumulate wealth are different, this leads to a different amount of aggregate wealth in equilibrium in each model. In the benchmark Aiyagari model the agents want to accumulate more wealth than our model, especially at the higher wealth levels. This is because there is more demand for precautionary saving in the benchmark model as all agents face the same EN rate of 3% per month and NE rate of 47% per month.

In our model, workers in safe jobs face lower exogenous job destruction rate of 2% and hence have lower precautionary savings motive. At the same time, these workers make it to the top of the wealth distribution more often as they have more time to save in employment than agents in risky jobs. The workers in risky jobs have a higher precautionary saving motive but they also lose their jobs more often and as a result of that cannot accumulate much more wealth. These differences in exposure to risk and the ability of agents to save their way away

Figure 7: Simulating non-employed workers with different starting wealth



(a) At borrowing constraint (b) At modal wealth (c) At maximum wealth

Panel (a) plots the equilibrium wealth distribution across non-employed and employed workers, with the combined sum of the area under the three lines summing to one. Panel (b) gives the unemployment rate at each wealth decile, defined as the fraction of workers in that wealth decile who are non-employed. Panel (c) gives the fraction of employed workers within each wealth decile who are employed in the risky job.

from the borrowing constraint shape how much precautionary savings there is in the aggregate. Because of these differences, the aggregate wealth is 3.20 in our model and 3.49 in the benchmark Aiyagari model implying a 9% difference in aggregate precautionary savings.

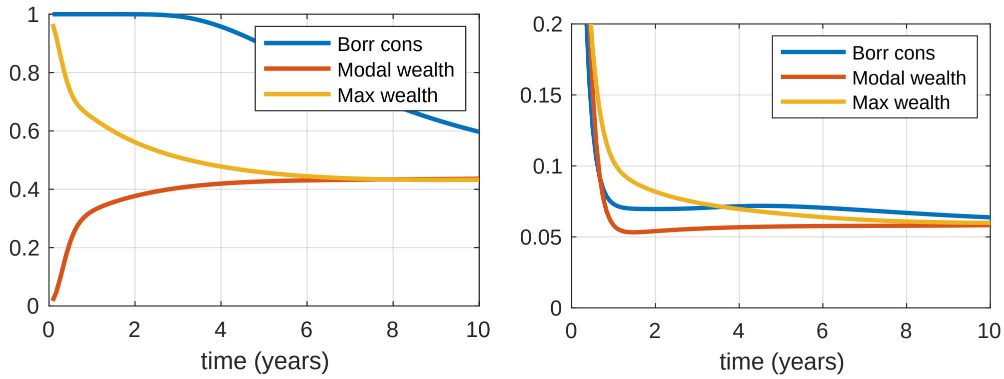
Another way of saying this is to recalibrate the interest rate r to keep the same amount of aggregate wealth. r is 2% annually in our calibration, and to keep the same amount of wealth in the Aiyagari model requires r to be 1.44% annually. This 25% decline in the interest rate is needed to discourage wealth accumulation to keep aggregate wealth the same in the two models, and shows just how important the structure of risk is in these models.

4.7 Result 4: Persistence of Wealth

Next, we take a unit mass of non-employed workers all with some initial wealth a_0 and simulate their experiences going forward over time. Their wealth distribution evolves as they gain and lose jobs, and eventually converges to the overall ergodic distribution. However, the convergence is slow and shows that one's current wealth has an important effect on one's future. We do this for three wealth levels: at the borrowing constraint, the mode of the wealth distribution, and the wealth level at which workers start wanting to quit. The wealth distribution are plotted in Figure 7. Even 3 years after the start of the simulation the wealth distribution of the non-employed who start at the borrowing constraint is still significantly to the left of the full ergodic distribution.

Part of the reason that the position in the wealth distribution is so persistent is that non-employed workers at different levels of wealth select different types of jobs, and hence have different employment experiences going forward. To see this, in Figure 8 we plot the fraction of the workers who are in risky jobs at each time since the start of the simulation, and the non-employment rate since the simulation. The three lines are now the three different starting wealths. In panel (a) we can see that the non-employed workers who start at the borrowing constraint select risky jobs (as we know) so 100% of those who find jobs are in risky jobs. What is more suprising is just how persistent this is: 100% remain in risky jobs for nearly three years. It is only from then on that the fraction in risky jobs starts to fall. In the model, 45% are in risky

Figure 8: Simulating non-employed workers with different starting wealth



(a) Fraction in risky job

(b) Unemployment rate

Panel (a) plots the equilibrium wealth distribution across non-employed and employed workers, with the combined sum of the area under the three lines summing to one. Panel (b) gives the unemployment rate at each wealth decile, defined as the fraction of workers in that wealth decile who are non-employed. Panel (c) gives the fraction of employed workers within each wealth decile who are employed in the risky job.

jobs in the true ergodic distribution, but after 10 years of simulation the workers starting from the borrowing constraint still are nearly 60% in the risky job. So wealth is very persistent, and has very persistent effects on the types of jobs workers select. The workers starting from modal wealth (red line) select the safe job so start with nearly 0% in the safe job , which more quickly rises towards normal levels. The wealthy workers (yellow line) also select the risky job, for reasons discussed, but as their wealth depletes they also quickly return to more normal distribution of jobs.

This has important effects on the employment experience going forward, as shown in panel (b). The plot is truncated to make the differences more visible. Notice how the workers starting from modal wealth quickly find jobs and their unemployment rate drops to 6% which is the calibrated non-employment rate. But the workers starting with low wealth (blue line) have a persistently higher non-employment rate for 10 years. The differences in non-employment rate come from the EU and UE rates of the two jobs: if a worker only ever searches for the risky job this rate would be 7% and if they ever search for the safe job it would 4.9%. So the higher non-employment rate of the low wealth workers is because most of them are stuck in the high risk jobs for a long period of time, and they therefore spend longer time laid off. This is very different from the Aiyagari model: future income and risk going forward is completely independent of one's current wealth in that model, unlike in ours.

5 Conclusions

In this paper we document a novel empirical relationship between a worker's wealth and their non-employment risk, and explore its implications for the sources of income and wealth inequality. Using the Panel Study of Income Dynamics we document a U-shaped pattern, whereby both lower wealth and the highest wealth workers have higher future non-employment risk than workers in the middle of the wealth distribution. We argue that this shows that workers unemployment risk and quit decisions respond to their wealth, and hence create a novel feedback from wealth inequality to income inequality.

The risk of becoming non-employed represents one of the greatest sources of income risk, to the extent that it is common in incomplete markets models to assume two exogenous income states representing employment and unemployment. Our contribution is to show that the risk of becoming non-employed is not exogenous to a worker's wealth, and we argue that low wealth workers face higher layoff risk, while high wealth workers voluntarily transition to non-employment more often through quits. We do so in a novel directed search model, where workers search for either risky but easy to find jobs, or safe but harder to find jobs. Low wealth non-employed workers trade off risk inter-temporally, and are willing to accept high layoff risk in the future in order to find a job faster and reduce the risk of remaining non-employed today.

Future work could investigate the implications for our findings for the optimal design of benefits policies, or the propagation of business cycle shocks. Making unemployment insurance asset-tested, and hence more generous for low wealth agents (Rendahl, 2012) would have additional benefits according to our data and model by allowing low wealth workers more time to search for safer jobs. This might help fight "low pay no pay cycles" of repeated unemployment and job instability for some workers.

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APPENDICES

A Empirical Appendix

A.1 Descriptive statistics

Here we present additional descriptive statistics on our sample.

Table A.1: Descriptive Statistics: Individual & Job Characteristics

	Mean	Std. Dev.		Mean	Std. Dev.
Demographics			**Industry**		
Age	39.36	11.45	Construction	0.07	0.25
Female	0.49	0.50	Manufacturing	0.21	0.41
Married	0.76	0.42	Transportation	0.09	0.28
Number of Children	0.91	1.13	Wholesale Trade	0.05	0.22
African American	0.08	0.27	Retail Trade	0.17	0.38
Other Ethnic Group	0.03	0.16	Finance	0.09	0.28
Years of Schooling	13.74	2.02	Services	0.33	0.47
Wage			**Occupation**		
Hourly Wage	21.41	29.19	Managerial & Professional	0.30	0.46
			Technical, Sales & Admin	0.33	0.47
			Service	0.11	0.31
			Precision Production, Craft & Repair	0.12	0.33
			Operatives & Labourers	0.14	0.34

Note: The sample contains 27,832 observations on 5,151 individuals. The sample includes individuals aged 18 to 65, who are only added to the sample once they join the labour market. They are then dropped from the sample once they leave the labour market and they do not appear again as employed. We restrict our sample to the core PSID sample who are not self-employed or working for the government or in farming related occupations. Lastly, our sample includes individuals which we observe for at least two consecutive waves. Monetary values expressed in 2015 US dollars.

A.2 Robustness Checks

A.2.1 Major Demographic Groups

A primary concern with our results could be that they are specific to certain demographic groups, or perhaps driven by composition effects across groups not captured by the way these groups are controlled for in our regressions. To show that this is not the case, in Table A.2 we present results from estimating (2) on key sub-samples. The U-shaped relationship is present for both men and women, for both single and married individuals, and for those with more than high school education. The results are relatively consistent across groups, with two notable exceptions. Firstly, while the elevated EN rate for the top wealth decile still has a positive and similar point estimate for individuals with a high school diploma or less (column 5), it is no longer statistically significant, while it is so for other groups. Secondly, the effects are much stronger for single workers relative to all other groups (column 3).

A.2.2 Life-cycle

It is well known that older workers have more stable employment, probably because they are better sorted into good matches, and so a natural question is whether the U-shape relationship that we found holds only at certain points of the life-cycle. We investigate the robustness

Table A.2: *EN* transitions in major demographic sub-samples

	(1) Men	(2) Women	(3) Single	(4) Married	(5) Low Edu.	(6) High Edu.
Low Wealth	0.029**	0.051***	0.070***	0.028**	0.067***	0.038***
	(0.014)	(0.015)	(0.020)	(0.011)	(0.021)	(0.012)
High Wealth	0.033***	0.036***	0.091***	0.023***	0.014	0.034***
	(0.012)	(0.013)	(0.030)	(0.009)	(0.016)	(0.011)
Observations	9949	9102	4405	14646	7502	11549
Individuals	2489	2341	1708	3924	2166	2955
R^2	0.071	0.078	0.090	0.052	0.094	0.055
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ïndividual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Occupation	Yes	Yes	Yes	Yes	Yes	Yes

* p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region, unless excluded due to collinearity with sample split. Industry and occupation dummies are based on 2-digit classifications. High Education are individuals who reported more than 12 years of completed schooling. Low Education individuals are those with 12 or less years of completed schooling.

of the U-shaped pattern to age in Table A.3. We split our sample to consider three different age groups: $18-34$, $35-49$ and $50-65$. For low wealth agents, the high *EN* risk persists throughout the life-cycle. The high wealth agents are more likely to experience an *EN*-switch in the two youngest groups, albeit we do not have enough power to tightly estimate the *High Wealth* coefficient in column (4).

A.2.3 Reverse Causality

While we control for many worker-level observables, it could be possible that reverse causality is responsible for the left part of the U-shaped relationship. To see why this could be the case, suppose that there are two types of workers: type H have permanently high *EN* rates, perhaps due to low productivity, and type L have permanently low *EN* rates. Next, let's assume that these types are uncorrelated with education, wages, and other observables, since we have already controlled for these in the main body of the paper. As shown in Section 3.3, making an *EN* transition causes one's wealth to fall, plausibly due to running down savings in non-employment. This could drive a spurious negative correlation between current wealth and a future *EN* switch through a composition effect: type H workers are likely to have low wealth, because they will have made more *EN* switches in the past, and are likely to make another *EN* transition in the future due to their permanent type. In this world, there is no causal link between *low* wealth and future *EN* switches, but a correlation driven by composition.

Table A.3: Focusing on the Tails of the Wealth Distribution by Age.

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	18 – 34	35 – 49	50 – 65	18 – 34	35 – 49	50 – 65
Low Wealth	0.049***	0.026*	0.062**	0.073***	0.035**	0.060*
	(0.015)	(0.016)	(0.028)	(0.015)	(0.016)	(0.034)
High Wealth	0.066**	0.031**	0.002	0.027	0.026**	-0.018
	(0.030)	(0.013)	(0.013)	(0.030)	(0.013)	(0.013)
Observations	7310	7681	4060	7310	7681	4060
Individuals	2789	2546	1298	2789	2546	1298
R^2	0.085	0.045	0.033	0.087	0.045	0.033
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Occupation	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

The permanent heterogeneity described above should manifest as presence of clusters of workers differentiated in the incidence of non-employment in their careers. We add various controls to specification (2) to test this possibility. Firstly, we introduce a dummy *Past EN Transition* which is equal to 1 if a worker has already experienced an *EN* transition. Essentially, this variable differentiates the first *EN* transition from all of the subsequent ones. Secondly, we construct a variable *Past Nonemployment Share* which is the ratio of number of interviews that a worker reported being in non-employment over the number of interviews up to and including wave t.[16] Thirdly, we construct a variable *Total Nonemployment Share* defined as ratio of interviews the individual reports non-employment over total number of their interviews in our sample. Compared to *Past Nonemployment Share*, this variable is both backward- and forward-looking.

We present the results of this exercise in Table A.4. The main finding is that we still find a statistically significant U-shaped relationship between wealth and *EN* transitions, even with these extra controls. Overall, our results suggest that part of the likelihood an individual experiences an *EN* transition could indeed be due to their inherent type. We infer this from the

[16]Note, we define this variable only for observations for which the individual is included in our sample, that is, after their first entry to the labour market and before they permanently leave it. In doing so, we also utilise information prior to 1997.

Table A.4: Controlling For Past and Future Non-Employment

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Low Wealth	0.037***	0.039***	0.027***	0.052***	0.055***	0.041***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)	(0.009)
High Wealth	0.036***	0.035***	0.025***	0.024***	0.023***	0.014*
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
Observations	19051	19051	19051	19051	19051	19051
Individuals	4830	4830	4830	4830	4830	4830
R^2	0.075	0.078	0.195	0.075	0.078	0.195
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Occupation	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.We additionally control for *Past EN Switch* in columns (1) and (4), *Past Nonemployment Share* in columns (2) and (5) and for *Total Nonemployment Share* in columns (3) and (6).

coefficients in Table A.4 being smaller than those estimated in Table 3. However, the U-shaped pattern is found to be robust to this extension as well.[17]

[17] We find statistically significant and positive coefficients on the new controls in all three cases (omitted in the Table), suggesting that they indeed capture the differences in individual-specific likelihood of experiencing an *EN* transition. Given objective data limitations this is the best one could do. Trying to address the reverse causality by introducing individual fixed effects is infeasible because of two reasons. Firstly, being in either the *Low Wealth* or *High Wealth* bin is highly persistent. Secondly, we have on average a bit more than 5 observations per individual in the sample.

B Online Appendix

B.1 Robustness of the U-shape

In this section we verify the robustness of our key empirical finding on the U-shaped relationship between wealth and likelihood to experience an EN-transitions.

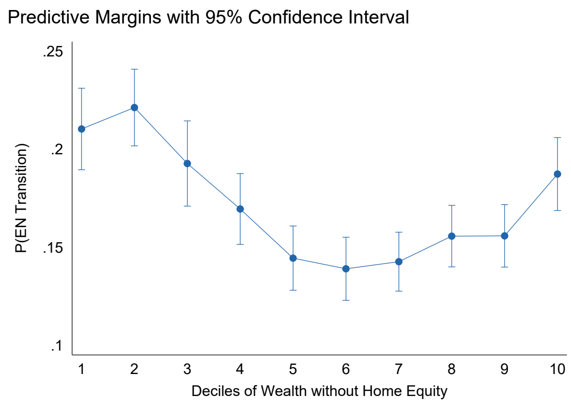
B.1.1 Definition of EN: including temporary layoffs

In the main text, we construct the EN variable in a way that eliminates temporary layoffs, both in the definition of unemployment and also by only looking for incidence of non-employment for workers who change jobs between interviews. The construction of the EN variable as in the main text therefore emphasizes permanent separations between employers and workers. Here we show that our main finding is robust to the less strict definition of EN transition.

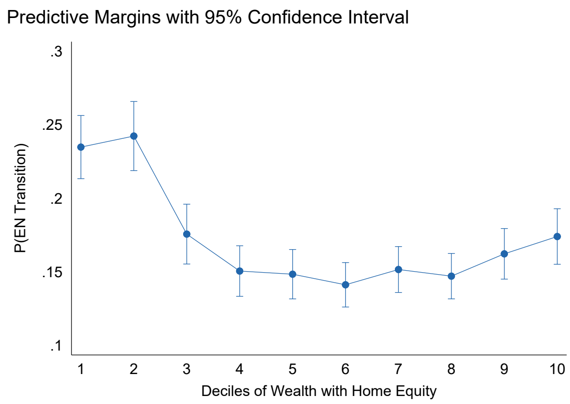
In the data, some workers report experiencing non-employment while being employed at interview in time t and $t+2$ *with the same employer*. This group of workers could have experienced either a temporary layoff, or a prolonged period of effectively unpaid leave. It is also likely that they were laid off, but later recalled. We decided not to include these episodes into our definition of the EN-transition dummy because of there being less certainty that the experience of non-employment in their case was unexpected/not pre-agreed. Nevertheless, as we demonstrate below, modifying the definition of the $EN_{i,t}$ dummy to include these episodes of non-employment does not overturn our main empirical finding.

The patterns reported on Figure B.1 are shifted upwards relative to Figure 2 which is the consequence of there being more EN-transitions in the data. However, the two Figures remain qualitatively similar, and so do Tables B.1 and 3.

Figure B.1: Margins of Deciles of wealth on the probability of an EN-transition (alternative definition of EN).



(a) Liquid Wealth



(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from an LPM regression as presented in equation 1 with less strict definition of the $EN_{i,t}$ dummy. Panel B.1a includes deciles of wealth without home equity, whilst Panel B.1b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

Table B.1: Focusing on the Tails of the Wealth Distribution (alternative definition of EN).

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Low Wealth	0.058***	0.042***	0.044***	0.097***	0.067***	0.068***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
High Wealth	-0.060***	0.032***	0.030***	-0.070***	0.023**	0.020**
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
Observations	20604	19128	19051	20604	19128	19051
Individuals	5008	4835	4830	5008	4835	4830
R^2	0.007	0.065	0.078	0.012	0.066	0.079
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes
Industry/Occupation	No	No	Yes	No	No	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective household wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

B.1.2 Wealth Distribution: ranking using household wealth

We construct the *Low Wealth* and *High Wealth* dummies based on the distribution of per-capita wealth in the paper. Here we show that under an alternative ranking of workers, one that uses household wealth instead, the U-shaped relationship between net wealth and EN-transitions prevails, see Figure B.2 and Table B.2.

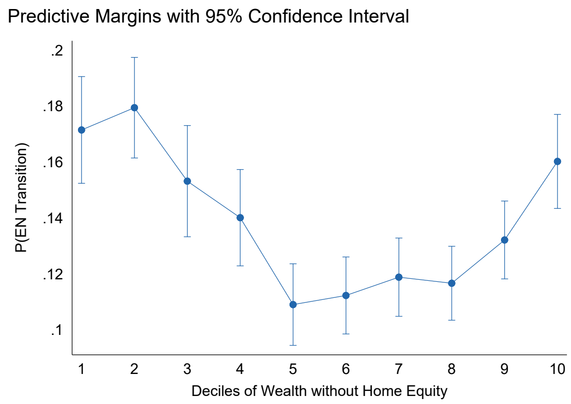
B.1.3 Sample selection: only including household heads

In the main body of the paper we included information on household heads and their spouses. This comes with the advantage of enlarging the sample size. However, some studies that use PSID data favour to focus on heads of the household only. For the sake of comparability, we show below that the novel finding on the U-shaped relationship between wealth and propensity to experience an EN transition prevails on such more constrained sample.

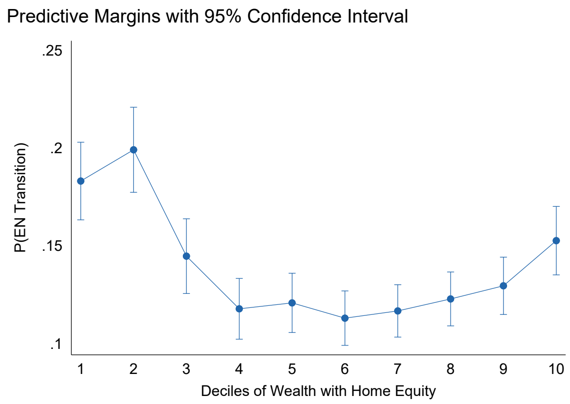
As the mapping between household net wealth and worker is now one-to-one, we derive workers' position on the wealth distribution using household net wealth. Analogously to the main text, we report results for two measures of net wealth. To begin with, we rerun the estimation producing Figure 2 in the main text. The results, which are displayed on Figure B.3, are similar, both qualitatively and quantitatively.

Next, we estimate equation (2) on the sample of household heads and report the results of doing so in Table B.3. Despite the sample size shrinking significantly, we nevertheless uncover a pattern strikingly similar to that reported in Table 3.

Figure B.2: Margins of Deciles of wealth on the probability of an EN-transition (household wealth).



(a) Liquid Wealth



(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from an LPM regression as presented in equation 1 with deciles based on household, and not per-capita wealth. Panel B.2a includes deciles of wealth without home equity, whilst Panel B.2b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

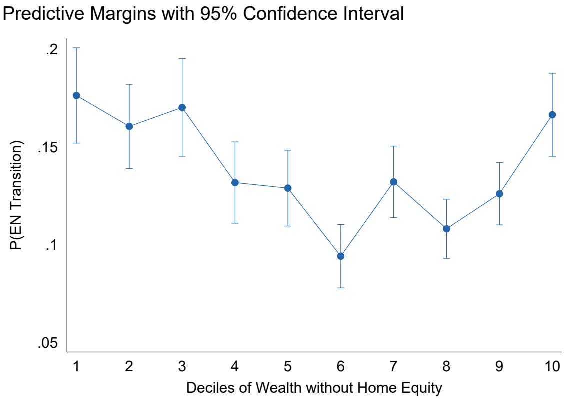
Table B.2: Focusing on the Tails of the Wealth Distribution (Household wealth).

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Low Wealth	0.046***	0.037***	0.039***	0.071***	0.048***	0.048***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
High Wealth	-0.052***	0.038***	0.035***	-0.055***	0.034***	0.030***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Observations	20604	19128	19051	20604	19128	19051
Individuals	5008	4835	4830	5008	4835	4830
R^2	0.006	0.063	0.070	0.008	0.063	0.070
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes
Industry/Occupation	No	No	Yes	No	No	Yes

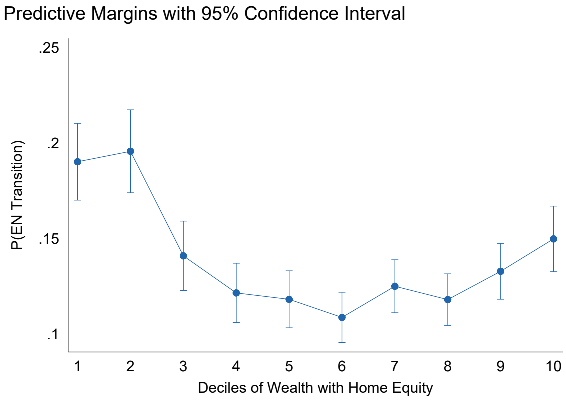
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Next to estimates we report marginal effects evaluated at mean values of other regressors. Low Wealth and High Wealth correspond to the bottom and the top decile of respective household wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

Figure B.3: Margins of Deciles of wealth on the probability of an EN-transition (Heads only).



(a) Liquid Wealth



(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from an LPM regression as presented in equation 1 ran on a sample of respondents who were classified as head of household. Panel B.3a includes deciles of wealth without home equity, whilst Panel B.3b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

Table B.3: Focusing on the Tails of the Wealth Distribution (Heads only).

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Wealth	0.059***	0.043***	0.045***	0.078***	0.051***	0.053***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)
High Wealth	-0.049***	0.046***	0.042***	-0.057***	0.036***	0.030***
	(0.010)	(0.011)	(0.011)	(0.009)	(0.011)	(0.011)
Observations	13616	12565	12516	13616	12565	12516
Individuals	3551	3423	3418	3551	3423	3418
R^2	0.008	0.073	0.081	0.010	0.073	0.081
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes
Industry/Occupation	No	No	Yes	No	No	Yes

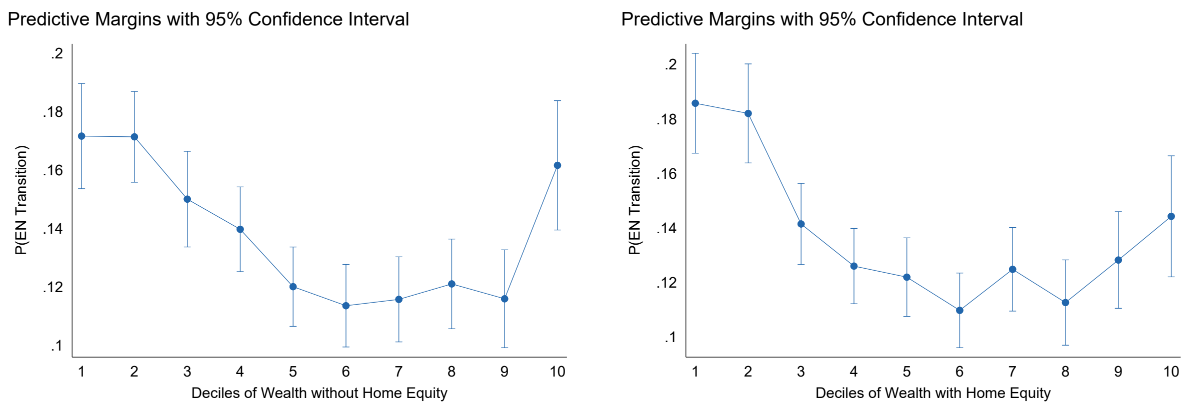
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Next to estimates we report marginal effects evaluated at mean values of other regressors. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

B.1.4 Alternative estimators: probit & logit

Our main variable of interest is the probability of a worker experiencing an EN-transition, as defined in the main text of the paper. The linear probability model, understandably, is potentially misspecified because it can predict values of this probability falling outside of the $[0, 1]$ range. To address this concern, we investigate the dependence of the probability of an *EN*-transition on wealth estimating probit and logit specification. The results, reported in Figures B.4 and B.5 and Tables B.4 and B.5 again indicate that the relationship of interest is a U-shaped one. The linear probability model only mildly overestimates the marginal effect of being in either *Low Wealth* or *High Wealth* bin on *EN*-transition. To see this, compare, for example, column (3) in Table 3 with tables reported here. In the main text, the estimated coefficients for the two dummies are 0.4 and 0.37, respectively, while the marginal effects implied by probit or logit estimates evaluated at mean values of regressors are a bit smaller (0.38 and 0.37 for probit and 0.37 and 0.34 for logit, respectively).

Figure B.4: Margins of Deciles of wealth on the probability of an *EN*-transition (Probit).



(a) Liquid Wealth

(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from a probit regression as presented in equation 1. Panel B.4a includes deciles of wealth without home equity, whilst Panel B.4b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

B.1.5 Alternative definition of the *Low Wealth* dummy

The U-shape relationship between per-capita wealth, visualised on Figure 2 in the main text can be considered asymmetric. The lowest two deciles of the net wealth distributions exhibit markedly higher incidence of *EN*-transitions than the rest of the distribution. In the paper, we specified the *Low Wealth* and *High Wealth* dummies to correspond to the bottom and the top decile, respectively. We now show that this was indeed a conservative choice.

Comparing the coefficients reported in columns (3) and (6) of Tables 3 and B.6 we find that the coefficients in the latter on both *High Wealth* and *Low Wealth* increase while remaining statistically significantly different from zero. This confirms that the definition of the *Low Wealth* dummy led to us underestimating the strength of the U-shape relationship.

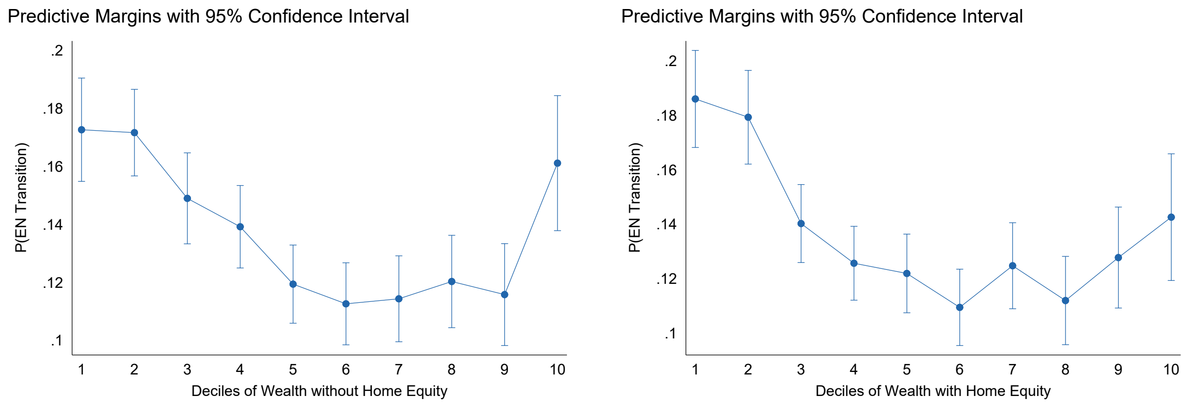
Table B.4: Focusing on the Tails of the Wealth Distribution (Probit).

	Wealth without Home Equity						Wealth with Home Equity					
	(1)		(2)		(3)		(4)		(5)		(6)	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Low Wealth	0.220***	0.054***	0.173***	0.037***	0.179***	0.038***	0.330***	0.085***	0.225***	0.050***	0.231***	0.051***
	(0.039)		(0.041)		(0.041)		(0.037)		(0.039)		(0.040)	
High Wealth	-0.216***	-0.042***	0.186***	0.040***	0.173***	0.037***	-0.279***	-0.052***	0.119**	0.025**	0.103*	0.021*
	(0.045)		(0.052)		(0.051)		(0.047)		(0.055)		(0.055)	
Observations	20604		19128		19051		20604		19128		19051	
Individuals	5008		4835		4830		5008		4835		4830	
Pseudo-R^2	0.007		0.075		0.083		0.012		0.075		0.083	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Individual Controls	No		Yes		Yes		No		Yes		Yes	
Industry/Occupation	No		No		Yes		No		No		Yes	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Next to estimates we report marginal effects evaluated at mean values of other regressors. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

Figure B.5: Margins of Deciles of wealth on the probability of an EN-transition (Logit).



(a) Liquid Wealth

(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from a logit regression as presented in equation 1. Panel B.5a includes deciles of wealth without home equity, whilst Panel B.5b includes deciles of wealth with home equity. Individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

B.2 Relationship between wealth and EN, EE, and NE transitions.

We now show that the U-shape dependence on wealth is a unique feature of EN transitions. To this end, we collect data on EE transitions (Employment-to-Employment) and on NE transitions (Non-employment-to-Employment). We identify EE transitions following the procedure that leads to detection of $E(N)E$ transitions. The difference here is that we set $EE_{i,t} = 1$ for workers who report being employed at the current interview date, report employment at a new job at the next interview and do not report any non-employment between interviews. We set $EE_{i,t} = 0$ for all other workers who are employed at the current and at the next interview date.

Table B.5: Focusing on the Tails of the Wealth Distribution (Logit).

	Wealth without Home Equity						Wealth with Home Equity					
	(1)		(2)		(3)		(4)		(5)		(6)	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Low Wealth	0.397***	0.054***	0.322***	0.036***	0.333***	0.037***	0.590***	0.085***	0.409***	0.048***	0.421***	0.049***
	(0.069)		(0.074)		(0.074)		(0.065)		(0.069)		(0.069)	
High Wealth	-0.412***	-0.042***	0.322***	0.036***	0.309***	0.034***	-0.539***	-0.052***	0.194*	0.021*	0.172	0.018
	(0.087)		(0.098)		(0.098)		(0.092)		(0.106)		(0.106)	
Observations	20604		19128		19051		20604		19128		19051	
Individuals	5008		4835		4830		5008		4835		4830	
Pseudo-R^2	0.007		0.076		0.084		0.012		0.077		0.084	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Individual Controls	No		Yes		Yes		No		Yes		Yes	
Industry/Occupation	No		No		Yes		No		No		Yes	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Next to estimates we report marginal effects evaluated at mean values of other regressors. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

Table B.6: Focusing on the Tails of the Wealth Distribution (*Low Wealth* as bottom 2 deciles).

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	β / SE	β / SE	β / SE	β / SE	β / SE	β / SE
Low Wealth	0.084***	0.051***	0.050***	0.123***	0.071***	0.069***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
High Wealth	-0.029***	0.044***	0.041***	-0.036***	0.031***	0.027***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Observations	20604	19128	19051	20604	19128	19051
Individuals	5008	4835	4830	5008	4835	4830
R^2	0.013	0.065	0.072	0.023	0.067	0.074
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes
Industry/Occupation	No	No	Yes	No	No	Yes

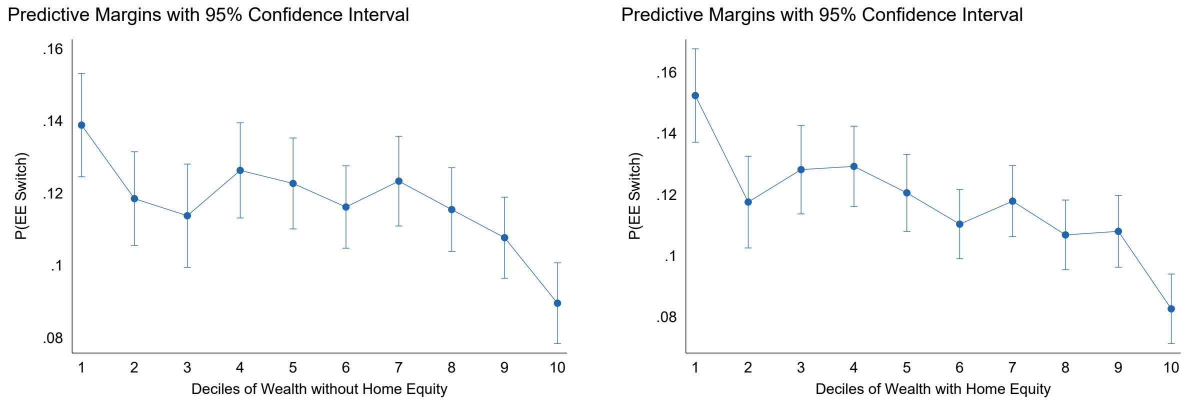
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth corresponds to the bottom two deciles and High Wealth to the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

The construction of the $NE_{i,t}$ dummy is the exact opposite of the EI and EU transitions. We set $NE_{i,t} = 1$ if a worker reports being non-employed at current interview and is found to be employed at the next interview date. Note, because of how survey is constructed, we do not observe $N(E)N$ transitions as non-employed workers are not asked about employment spells between interview dates.

Figure B.6 presents the results of an exercise analogous to that presented on Figure 2 in the main body of the paper but with the probability of experiencing an *EE* transition as the dependent variable. Here, we do not see a U-shaped pattern, but a clear evidence of the likelihood of experiencing an *EE* transition to decline in wealth.

Figure B.6: Margins of Deciles of wealth on the probability of an EE-Transition

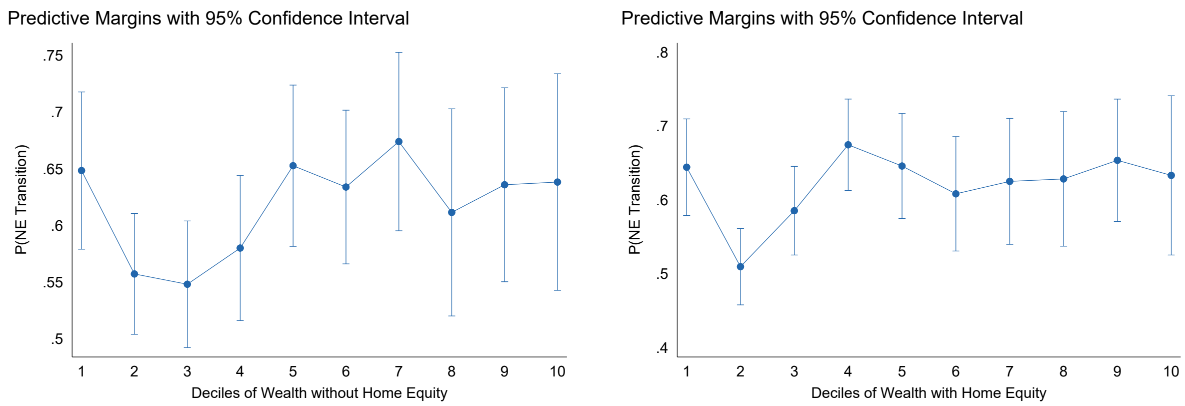


(a) (b)

Note: These figures plot the predictive margins on deciles of wealth from a linear probability model regression as presented in equation 1 with the EE_{it} dummy as the dependent variable. . Panel 2a includes deciles of wealth without home equity, whilst Panel 2b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

Figure B.7 presents the results of an exercise analogous to that presented on Figure 2 in the main body of the paper but with the probability of experiencing an *EN* transition as the dependent variable.

Figure B.7: Margins of Deciles of wealth on the probability of an NE-Transition



(a) (b)

Note: These figures plot the predictive margins on deciles of wealth from a linear probability model regression as presented in equation 1 with the NE_{it} dummy as the dependent variable. . Panel 2a includes deciles of wealth without home equity, whilst Panel 2b includes deciles of wealth with home equity. Year fixed effects, individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level. Data is from waves 1999-2017 of the PSID.

Finally, we make a more formal comparison in Table B.7. Columns (1) and (4) repeat the result from the main text. Columns (2) and (5) are concerned with the effect of *Low Wealth* and *High Wealth* on NE-transitions. While the estimated coefficients are positive, they are not significantly different from zero. Finally, we find a starkly different pattern in columns (3) and (6), the likelihood of experiencing an EE-transition is found to decline significantly with wealth.

Table B.7: Focusing on the Tails of the Wealth Distribution: EN versus EE and NE.

	Wealth without Home Equity			Wealth with Home Equity		
	(1)	(2)	(3)	(4)	(5)	(6)
	EN	NE	EE	EN	NE	EE
Low Wealth	0.040***	0.052	0.028***	0.056***	0.051	0.030***
	(0.010)	(0.037)	(0.009)	(0.011)	(0.035)	(0.010)
High Wealth	0.037***	0.028	-0.022***	0.025***	0.015	-0.026***
	(0.009)	(0.050)	(0.007)	(0.009)	(0.056)	(0.007)
Observations	19051	2077	19051	19051	2077	19051
Individuals	4830	1223	4830	4830	1223	4830
R^2	0.070	0.065	0.046	0.070	0.065	0.046
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Occupation	Yes	Yes	Yes	Yes	Yes	Yes

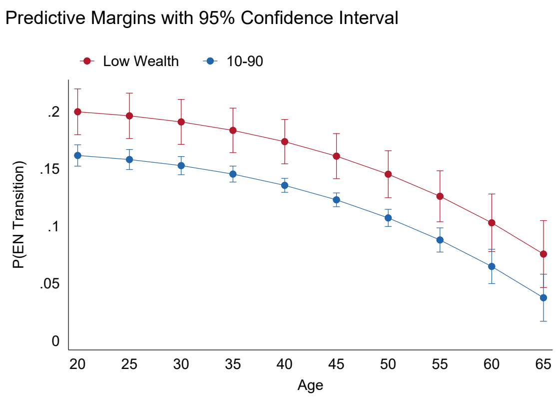
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Low Wealth and High Wealth correspond to the bottom and the top decile of respective wealth distribution. Base group is the remainder of the wealth distribution. Individual controls include age, education, female, race, marital status, number of children, hourly wage, and region. Industry and occupation dummies are based on 2-digit classifications.

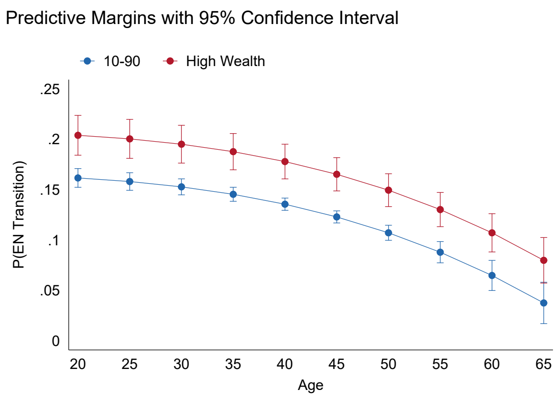
B.3 Additional Tables and Figures

Life-Cycle We re-estimate specification (2) for subsamples of different ages, taking five year age bins from age 20 to 65. We plot the results in Figure B.8, with panel (a) comparing the estimated EN probabilities for the bottom decile with the middle deciles, and panel (b) doing the same for the top decile. The general pattern conveyed by the figures is that the excess EN rate of the bottom and top wealth deciles is present across most of the age distribution. The figures reveal that the EN rate is declining for all wealth deciles as workers age, as is to be expected. At every wealth decile the point estimate for the bottom and top deciles is greater than the middle deciles, as with our main finding. As workers age the gap shrinks, and the confidence intervals begin to overlap from age 60 onwards, suggesting that the effect is smaller for the oldest workers.

Figure B.8: *EN* Transitions across the Life-cycle



(a) Bottom 10% vs. 10-90%



(b) Top 10% vs. 10-90%

Note: These figures plot the predictive margins on deciles of wealth from a regression as presented in equation 1 with the corresponding 95% confidence interval. Where the dependent variable is whether respondent experienced an *EN* switch, but for the margins across age groups. Panel B.8a compares the bottom 10% of the wealth distribution to the centre and Panel B.8b compares the top 10% of the distribution to the centre. Individual controls and a full set of industry and occupation controls are included. Standard errors are clustered at the individual level.