Wealth, Quits and Layoffs*

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Abstract

Using worker-level panel data we document that current wealth predicts the probability that a worker transitions from employment to non-employment. We find a surprising U-shaped pattern: Low-wealth workers face higher probability than the median worker, but so do the high-wealth workers. This result 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 inequalities. 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
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1 Introduction

Many countries, including the United States, 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 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. 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.[2]

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 drastic and persistent reductions in wealth for all but the wealthiest workers. For example, for workers in the bottom 90% of the wealth distribution, making an EN transition is associated with total net wealth falling by approximately 75% in the following two years, with this effect persisting up to six years. While this number is large, recall that many workers in the US hold very little wealth, and thus a non-employment spell has the potential to wipe out a large fraction of a small wealth holding. This finding completes the identification of the "feedback" logic between wealth and EN risk in the data: EN transitions lead to lower wealth, and lower wealth then affects (in a non-monitone way) one's future probability of making EN transitions.

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

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

Before discussing our empirical results and their robustness in more depth, it is worth asking what relationship one would expect to see between current wealth and the probability of making an *EN* transition in the future. Two plausible hypotheses both suggest an upwards sloping relationship between wealth and *EN* probability, making the U-shaped pattern initially surprising. Firstly, a standard "wealth effect" hypothesis would suggest that the higher one's wealth, the less they are willing to work, and hence the higher the probability of making an *EN* transition (Algan et al., 2003; Rendon, 2006). Secondly, a "precautionary saving" hypothesis would suggest that workers in higher non-employment risk jobs should save more and accumulate more wealth in order to insure themselves against this risk (Larkin, 2019). While both of these features will play a role in our model, clearly neither can explain the downwards sloping part of the U shape where higher wealth leads to lower *EN* probabilities. Thus, our basic empirical finding is non-trivial to explain, which motivates our new quantitative model.

We explore robustness and extensions of our main result along several dimensions. Firstly, our basic regressions all control for current wage, which is an important confounder given that wage and wealth will be highly correlated. Secondly, the result holds across the entire life-cycle, and within major demographic groups such as male versus female or single versus married. Thirdly, we present suggestive evidence that the *EN* transitions we study are more due to layoffs for low wealth workers. This supports the interpretation that our U-shape is driven by elevated *layoff risk* for low wealth workers, but elevated *quits* for high wealth workers.

A very important consideration is whether our results could be driven by a simple omitted variable bias due to persistent differences in types across workers as in Morchio (2020). For example, it could be that there are two types of workers, one which has a permanently higher *EN* risk than the other. Since becoming non-employed in the past is likely to reduce one's current wealth, this could create a mechanical correlation between current wealth and future *EN* risk. High *EN* risk type workers would then be likely to both 1) have made an *EN* transition in the past, and hence have low wealth today, and 2) make another *EN* transition in the future, due to their unobserved type. To address this concern, we first note that we control for all of the standard worker and job characteristics to remove observable differences. As a further robustness, we additionally control for past *EN* switches in the regression, using various specifications, as this should capture the persistent unobserved type difference mentioned above. Our results are very similar even with this extra control, suggesting that unobserved heterogeneity is not driving our results. Given this finding and the fact that our regressions associate current wealth with *future EN* transitions, we thus tentatively conclude that there is a causal link from wealth to non-employment risk.

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.[3] We additionally incorporate a fix cost of working, which drives quit to unemployment for sufficiently wealthy workers.

Our key assumption is that there are two kinds of jobs: "risky" jobs and "safe" jobs. We set up a reduced-form search problem inspired by directed search, where non-employed workers can only search for one kind of job at a time. Safe jobs have low unemployment risk (i.e. a low EN rate), but are harder to find because they have a low job offer arrival rate (NE rate). Risky jobs, on the other hand, are less safe because they have a higher EN rate, but are also easier to find, which we model as a higher NE rate. 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, by raising the EU rate of low wealth workers. 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, by raising the quit rate of high wealth workers. Put together, we find that reasonable parameter values are able to replicate the U shape from the data very well. Moreover, the model mechanisms are consistent with our suggestive evidence that layoffs are more important at low wealth levels while quits are at high wealth levels.

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 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 exogenous, the costs of incomplete markets in this model are more severe because of how income risk correlates with wealth. When income risk is exogenous, all agents have 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

[3] 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.

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 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.[4] 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 whenver 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.

[4] The Panel Study of Income Dynamics is a public use dataset, produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor. The PSID can be accessed and downloaded at https://psidonline.isr.umich.edu.

[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: Descriptive Statistics: Labour Market Status and Flows

	Mean	Std. Dev.		Mean	Std. Dev.
Labour Market Status			**Type of EN transition**		
Unemployed	0.051	0.220	EU	0.039	0.194
Inactive	0.039	0.194	EI	0.021	0.144
			E(N)E	0.079	0.270
Transitions from E			Involuntary	0.030	0.171
EN	0.140	0.347			
EE	0.119	0.324			

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.

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 waves t and $t+1$ 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 wave $t+1$. If they report being either unemployed (U) or inactive (I), we set $EN_{i,t} = 1$. If, however, they report being employed 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 waves t and $t+1$. 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 at wave 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*. For a more complete picture, we also collect data on *EE* transitions which require the respondent to change employers between waves and absence of a non-employment spell in the meantime. Finally, we also distinguish voluntary and involuntary *EN* transitions. We present the summary of labour market status and flows in our sample in Table 1. Approximately 9% of our sample is non-employment. A quarter of workers 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. A bit less than one-quarter of *EN* transitions are involuntary.

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. As home equity is harder to tap into than, say, cash or stocks, the first wealth variable proxies for the liquid part of net wealth. Furthermore, we collect information on hourly wage at the main job at time of interview. All monetary variables are expressed in 2015 US dollars.

We are also interested in a standard set of demographic characteristics to be used as additional covariates in our regressions. To this end, we keep information on gender, age, marital status, number of children, ethnicity, and educational attainment in the data. Last, but not least, we will also include industry and occupation controls, where these are measured using aggregated census industry and occupation codes to the 2 digit level. We report descriptive statistics of our sampe in Table A.1 together with a more detailed information on wealth and wage distributions in Table A.2.

3 Empirical Results

In this section, we empirically investigate the relationship between wealth and EN transitions using the PSID data. First, we estimate the probability of an EN transition across the entire wealth distribution. Then, we focus at the top and bottom deciles and document that making an EN transition comes with

additional robustness and sample restrictions, including life-cycle patterns and demographics. Following this discussion, we provide evidence that the observed greater probability of an EN transition at the bottom of the wealth distribution is driven more by involuntary separations than it is at the top of the wealth distribution. Finally, we discuss the consequences of EN switches on future wealth and wages.

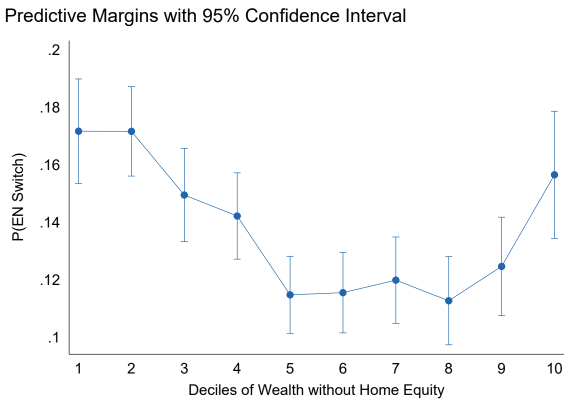
3.1 Estimation Strategy

Our main estimation specification can be summarised in the following regression:

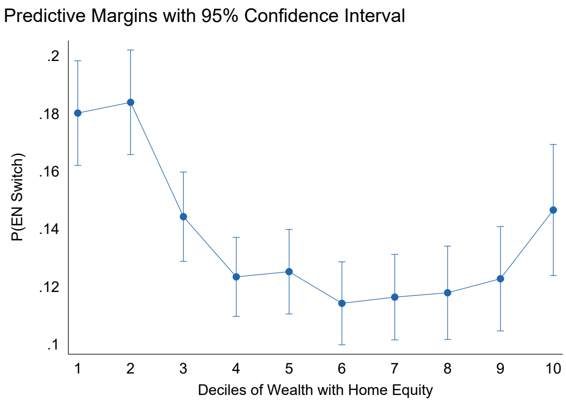
$$Pr(EN_{i,t}|Wealth_{h(i),t}, \mathbf{X}_{i,t}) = \Phi\left(\sum_{d=1}^{D} \delta_d W^d_{h(i),t} + \mathbf{X}'_{i,t}\boldsymbol{\beta}\right) \tag{1}$$

This regression estimates the determinants of the probability of observing an EN switch for individual, i between time t and $t+1$, coded as our 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 wealth of the household h the individual belongs to, $Wealth_{h(i),t}$, where we use either liquid or total net wealth. In our regressions we consider indicator functions equal to one if $Wealth_{h(i),t}$ belongs to bin d of the wealth distribution which we denote $W^d_{h(i),t}$. The coefficients δ_d capture the effect of belonging to wealth bin d on the probability of making an EN switch. 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 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 and for log hourly wage. Standard errors are

Figure 1: Margins of Deciles of wealth on the probability of an EN-Switch



(a) Liquid Wealth



(b) Total Wealth

Note: These figures plot the predictive margins on deciles of wealth from a regression as presented in equation 1. Panel 1a includes deciles of wealth without home equity, whilst Panel 1b 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.

clustered at the individual level. Our preferred specification is a Probit hence Φ refers to the Cumulative Normal Standard Distribution Function but our results are robust to the use of alternative specifications, see Tables A.3 and A.4.

3.2 EN Transitions as a Function of Wealth

To begin with, estimate our baseline specification (1) splitting the wealth distribution into deciles. We then plot the marginal effects of being in a given wealth decile holding other variables constant at their means in Figure 1. Panel (a) represents the results using liquid wealth, and Panel (b) 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-switch 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.[7]

The figures give 95% confidence bands, showing that the results are 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 at least one EN transition in the two years between sample waves. For workers in the bottom wealth decile this is closer to 17%, meaning a bit less than 50% increase in their EN rate. Similarly, for workers in the top wealth decile their EN

[7]We show that the relationship between wealth and EN transitions is very different from how wealth impacts on the likelihood of an EE transition in Appendix A. As can be seen on Figure A.1 and Table A.5, we find a purely downwards sloping relationship between EE switches and both wealth measures across all wealth deciles. This agrees with the results of Lise (2013) and Griffy (2021), and we extend their results by performing a less parametric examination using wealth deciles.

Table 2: Focusing on the 10%-Tails of the Wealth Distribution.

	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
Bottom 10	0.188***	0.046***	0.171***	0.037***	0.179***	0.038***	0.282***	0.072***	0.200***	0.044***	0.205***	0.045***
	(0.039)		(0.042)		(0.042)		(0.038)		(0.040)		(0.040)	
Top 10	-0.273***	-0.052***	0.168***	0.036***	0.153***	0.032***	-0.294***	-0.055***	0.140**	0.030**	0.123**	0.025**
	(0.045)		(0.052)		(0.052)		(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		0.074		0.082		0.010		0.075		0.083	
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. Base group is the middle of the distribution. Individual controls include age, education, female, race, married, children, region and year. Columns (1)-(3) consider wealth bins without home equity, in columns (4)-(6) wealth bins are worked out with the inclusion of home equity.

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 1, 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 specification:

$$Pr(EN_{i,t}|Wealth_{h(i),t}, \mathbf{X}_{i,t}) = \Phi\left(\alpha + \delta_1 W^1_{h(i),t} + \delta_{10} W^{10}_{h(i),t} + \mathbf{X}'_{i,t}\boldsymbol{\beta}\right). \tag{2}$$

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 present the results of estimating Equation (2) in Table 2 which shows the estimated coefficients δ_1 and δ_{10} 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 main 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 3.8 p.p. and 3.2 p.p. higher, respectively. These marginal effects agree closely with the differences in EN rates across the whole wealth distribution shown in Figure 1. 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, so these numbers simply reflect the correlations between wealth and probability of an EN switch. 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 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

In theory, the U-shaped relationship between wealth and the probability of making an EN transition, while statistically significant, need not matter for wealth accumulation and the strength of the precautionary savings motive. To investigate this formally, we exploit the panel nature of our dataset, and run regressions of realised EN switches on future wealth at various horizons. Specifically, we estimate:

$$\text{arcsinh}(W_{h(i),t+y}) = \boldsymbol{X}'_{i,t}\boldsymbol{\beta}_y + \gamma_{1,y}EN_{i,t} + \gamma_{2,y}EE_{i,t} + \varepsilon_{i,t} \tag{3}$$

The dependent variable is the inverse hyperbolic sine of wealth y years in the future, denoted as $\text{arcsinh}(W_{h(i),t+y})$ for individual, i, at $t+y$ year.[8] We regress this on the standard controls, as well as the indicator for whether the individual experienced an EN transition between time $t-2$ and t, denoted $EN_{i,t}$. Since workers also make EE transitions, which could affect their wealth, we control for these too.

The main coefficient of interest in Equation (3) is $\gamma_{1,y}$. This shows the effect on an individual's wealth y years in the future of having experienced an EN switch at time t. The comparison group is workers who did not experience an EN switch. Since waves are every two years, we run this regression for $y = 2$, 4, and 6, and estimate coefficients for each horizon. There is a reduction in sample size as we increase the horizon, which means that estimates become less precise the further ahead we look.

The results of these regressions are presented in Table 3, with columns 1 to 3 giving the results for liquid net wealth and 4 to 6 for total netwelth. We additionally distinguish between wealth deciles at the time of the EN switch, to identify whether EN switches have different effects on future wealth for low-wealth, middle-wealth and high wealth individuals. The main result is presented in columns 2 and 4, which gives the effect of an EN switch on future wealth for the majority of workers in the economy, those between the 10th and 90th wealth percentile at the time of their switch. The results are dramatic, with an EN switch being associated with statistically significant and economically very large and persistent declines in wealth.

[8] We use the inverse hyperbolic sine here as a value of zero or negative is informative and we do not want to disregard these observation as we would with the log. The interpretation of the coefficients here would be the same as if we had taken the log. See Bellemare and Wichman (2020) for a discussion of this.

Table 3: Change in real wealth between year t and year:

	Wealth without Home Equity			Wealth with Home Equity		
	(1) Bottom 10	(2) 10-90	(3) Top 10	(4) Bottom 10	(5) 10-90	(6) Top 10
$t+2$	-0.685	-1.390***	-0.580	-1.843***	-1.891***	-1.059
	(0.662)	(0.248)	(1.124)	(0.632)	(0.251)	(1.215)
N	1823	15461	1767	1828	15469	1754
$t+4$	-1.919**	-1.110***	-0.169	-1.638**	-1.817***	0.169
	(0.751)	(0.287)	(1.304)	(0.689)	(0.293)	(1.339)
N	1308	12181	1276	1346	12157	1262
$t+6$	0.201	-1.510***	-0.083	-0.293	-2.449***	1.406
	(1.131)	(0.385)	(1.813)	(1.061)	(0.405)	(1.598)
N	624	7106	614	605	7127	612

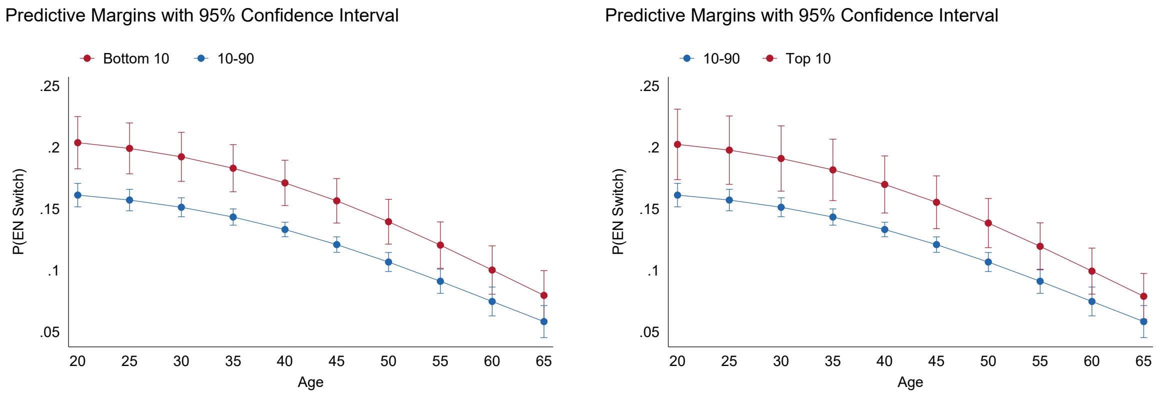
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Base group is individuals who do not experience an EN transition. Individual demographic and industry/occupation controls are included in all specifications.

A coefficient value of x implies that an EN switch leads to an $100 \times (e^x - 1)\%$ change in wealth. Thus, column 2 shows that for the majority of workers, an EN switch leads to a 75% reduction in wealth two years later, a 67% reduction four years later, and a 77% reduction six years later relative to the reference group. Thus, transitioning from employment to non-employment leads to a significant and very persistent reduction in wealth, which appears to last at least six years with very little evidence of recovery. This finding might not be initially surprising, as it is natural to suppose that leaving employment will lead to lower wealth because people earn less in non-employment (for example through benefits) than they do when employed. But the persistence of these effects is quite striking, underscoring just how permanent an effect on a worker's economic life non-employment spells can have. Moreover, from a theoretical point of view the large effect that losing employment has on wealth is consistent with the idea that workers are not able to insure themselves against idiosyncratic income risk.

The remaining columns give nuance and additional interpretation to this idea. In column 1 we present the same result but for workers who were in the bottom decile of the wealth distribution at the time of their EN transition. We find a much smaller and not statistically significant effect of the EN transition on wealth two years later for these workers. This could be because workers in this wealth decile already have such low wealth that they have little left to lose when they become non-employed. For these workers, the loss of income from non-employment cannot be cushioned by running down savings, suggesting that they have to reduce their consumption during non-employment spells.

Figure 2: *EN* Switches 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 2a compares the bottom 10% of the wealth distribution to the centre and Panel 2b 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.

The findings reported in column 3 show that the wealthiest workers seem not to fare worse than those who have not experience a non-employment spell. There can be several explanations of this fact, we believe the following two (not mutually exclusive) are most plausible. Firstly, these workers have such high levels of wealth that a non-employment spell makes only a small dent in it. Secondly, the non-employment spells of the wealthiest workers are shorter.

The difference between the wealthiest workers and the rest become more visible when one considers total net wealth. Columns 4 and 5 contain evidence of the bottom 90% faring significantly worse following an *EN* transition. Thus, we have identified that declines in wealth leads to higher *EN* risk for low wealth workers, this establishes the existence of a novel feedback mechanism which can trap workers in low wealth.

3.4 Robustness Checks

3.4.1 Life-cycle

The first additional analysis we consider is how our result varies over the lifecycle. 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.

To do so, 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 2, 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

Table 4: Controlling For Past Non-Employment

	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
Bottom 10	0.169***	0.036***	0.181***	0.039***	0.157***	0.031***	0.188***	0.040***	0.202***	0.044***	0.163***	0.033***
	(0.041)		(0.042)		(0.043)		(0.039)		(0.040)		(0.041)	
Top 10	0.149***	0.031***	0.145***	0.030***	0.126**	0.024**	0.119**	0.024**	0.113**	0.023**	0.086	0.016
	(0.050)		(0.051)		(0.051)		(0.053)		(0.055)		(0.055)	
Previous EN	0.289***	0.058***					0.286***	0.057***				
	(0.033)						(0.033)					
Past Nonemp. Share			0.865***	0.172***					0.861***	0.171***		
			(0.087)						(0.087)			
Total Nonemp. Share					4.735***	0.880***					4.729***	0.879***
					(0.143)						(0.143)	
Observations	19051		19051		19051		19051		19051		19051	
Individuals	4830		4830		4830		4830		4830		4830	
Pseudo R^2	0.088		0.090		0.191		0.089		0.091		0.191	
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. Base group is the third wealth quintile group. Individual controls include age, education, female, race, married, children, region and year. Each group refers to a different aggregation of the Industry and Occupation codes in order to include additional wave of data with consistent coding.

than the middle deciles, as with our main finding. As workers age the gap shrinks, and the confidence intervals begin to overlap from age 55 onwards, suggesting that the effect is smaller for the oldest workers.[9]

An additional benefit of looking at these life-cycle effects is that it also also emphasises 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 (recall we measure wealth at the household level) rather than wealth they have personally accumulated over time from employment. Hence, the finding that wealth affects EN switches 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. We stress that we control for log wages in our baseline specification, and investigate unobserved heterogeneity in the next section, but still view the lifecycle results as useful additional validation.

3.4.2 Unobserved Heterogeneity

While we control for many worker-level observables, it could be possible that unobserved heterogeneity drives our results. In this section we discuss and build an intuitive test for such a channel, and find that it does not affect our main results.

Specifically, our results concern the effect of time t wealth on a EN transition, and so one could be concerned about how unobserved heterogeneity creates a form of reverse causality from EN switches to wealth. The channel we have in mind is the following. 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. These rates differences have to be uncorrelated with education, wages, and other observables, since we already control for these

[9] In Table A.6 we repeat the formal tests from specification (2) on three different age bins ($18-34$, $35-49$ and $50-65$). The results confirm the graphical analysis. The U-shape is much stronger for the youngest group.

Table 5: *EN* Switches for different samples

	(1) Men		(2) Women		(3) Single		(4) Married		(5) High School or Less		(6) More than High School	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Bottom 10	0.227***	0.045***	0.199***	0.047***	0.274***	0.080***	0.193***	0.038***	0.291***	0.074***	0.197***	0.039***
	(0.060)		(0.058)		(0.078)		(0.049)		(0.073)		(0.050)	
Top 10	0.169**	0.033**	0.120*	0.028*	0.323*	0.096*	0.108**	0.020**	0.061	0.014	0.137**	0.027**
	(0.073)		(0.072)		(0.172)		(0.054)		(0.096)		(0.061)	
Observations	9934		9102		4405		14646		7502		11549	
Individuals	2487		2341		1708		3924		2166		2955	
Pseudo R^2	0.082		0.080		0.080		0.062		0.093		0.066	
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. Base group is the third wealth quintile group. Usual Individual controls are included. More than High School are individuals who reported more than 12 years of completed schooling.

in our regression. As shown in Section 3.3, making an *EN* transition leads one's wealth to fall, 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 wealth and future *EN* switches, but a correlation driven by composition.

To rule out this possibility, we need to control for the type of permanent heterogeneity described above. Since this should manifest as different individuals having had different numbers of *EN* switches in the past, we can control for this by controlling for measures of past *EN* switches in our regressions. Intuitively, the unobservable permanent type differences are proxied with observable past *EN* transition measures with which they are correlated. We add various controls to specification (2) to test this possibility. Firstly, we introduce a dummy *Past EN Switch* 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.[10] Thirdly, we construct a variable *Total Nonemployment Share* which captures the length of time an individual spent in nonemployment over their employment history. Note, unlike the first two variables, this one is not only backward- but also forward-looking.

We present the results of this exercise in Table 4. The main finding is that we still find a statistically significant U-shaped relationship between wealth and *EN* switches, even with these extra controls with the exception of column 6 where the point estimate coefficient for the *Top 10* variable is positive, but no longer significant. Overall, our results suggest that part of the likelihood an individual experiences an *EN* transition is indeed due to their inherent type. Some workers seem to be persistently more likely than others to experience non-employment. However, this does not fully explain the U-shaped pattern.

[10]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 6: $E(N)E$ versus EU and EI Transitions

	Wealth without Home Equity						Wealth with Home Equity					
	E(N)E		EU		EI		E(N)E		EU		EI	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Bottom 10	0.204***	0.029***	0.069	0.005	0.038	0.001	0.218***	0.031***	0.152***	0.012***	-0.038	-0.001
	(0.047)		(0.062)		(0.079)		(0.044)		(0.057)		(0.078)	
Top 10	0.125**	0.017**	0.101	0.008	0.147	0.006	0.125*	0.017*	-0.011	-0.001	0.188**	0.008**
	(0.061)		(0.075)		(0.092)		(0.064)		(0.086)		(0.093)	
Observations	19051		19048		16888		19051		19048		16888	
Individuals	4830		4830		4490		4830		4830		4490	
Pseudo R^2	0.069		0.073		0.105		0.070		0.074		0.105	
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. Base group is the middle of the distribution

In all three cases we find statistically significant and positive coefficients on the new control. This shows that, even with all of our standard controls, there are some differences in EN rates across individuals which are persistent, and hence captured by adding past EN switches to the regression. This validates that the type of reverse causality we worried about could have been an issue. However, these effects are sufficiently small that our estimated relationship between wealth and future EN switches remains similar with the new controls. The largest differences comes from adding total time in unemployment as a control, but even in this case the coefficients only drop from 0.038 to 0.031 for the bottom decile and 0.032 to 0.024 for the top decile. We interpret this as strong evidence that our findings are not driven by reverse causality from unobserved heterogeneity, and that there is a causal link from wealth to EN transitions.

3.4.3 Major Demographic Groups

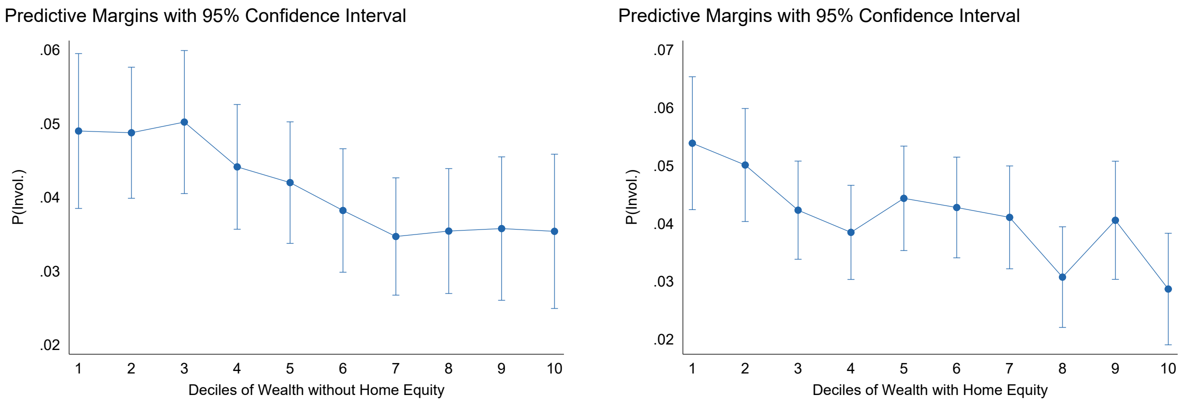
Another concern with our results could be that they are specific to certain demographic groups, or perhaps driven by composition effects across groups not captured by the way these groups are controlled for in our regressions. To show that this is not the case, in Table 5 we present results from specification (2) run on key subsamples.

We see that the U-shaped relationship is present within major sub-samples: it 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).

3.5 Understanding the Transitions

Having established the existence, significance and robustness of our main result, we turn to understanding its drivers. To do this, we dig deeper into the characteristics of EN transitions

Figure 3: Margins of Deciles of Wealth on the Probability of an Involuntary Separation



(a) (b)

Note: These figures plot the predictive margins on deciles of wealth from a regression as presented in equation 1, where the dependent variable refers to whether the respondent had an involuntary job separation. Panel 1a includes deciles of wealth without home equity, whilst Panel 1b 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. Switches are classified as voluntary or involuntary based on the responses to survey questions on what happened in their previous employment or whether they experienced being laid off.

by looking at their main sub-categories. The results of this exercise are presented in Table 6. The U-shaped pattern is confirmed for the $E(N)E$ transitions for both types of wealth. The remaining two types of EN transitions are much less frequent and hence objectively there is less variation there. On top of that, it seems that particularly the EN switches overlap to a greater extent with other individual-specific characteristics which shrinks the estimation sample size by approximately one-sixth. Nevertheless, we uncover suggestive evidence regarding the propensity to experience an EU transition at the bottom of the wealth distribution and an EI transition at the top. This only holds for total net wealth, though.

While this is not a clear-cut partition, we find it plausible to argue that transitions to inactivity are voluntary while those to unemployment are not. To make further progress towards understanding the EN transition, we complement this exercise by looking into the propensity to experience an involuntary EN transition. The results are presented in Figure 3, again performed for both liquid and total wealth. We see that, for both wealth measures, lower wealth individuals are more likely to experience involuntary separations relative to higher wealth individuals. While the pattern of point estimates points in this direction, the confidence intervals are overlapping so we stress that this evidence is suggestive, and worthy of further investigation. Additionally, the total fraction of workers reporting at least one involuntary separation between waves is very low, at around 5%, so it is possible that the measurement of involuntary separations in the data is imprecise.

3.6 Summary of empirical results

In summary, we have shown the following empirical results. We identified a novel U-shaped relationship between current wealth and the probability of making an employment to non-employment transition. Using a large number of controls and robustness exercises, we argue that this relationship is likely to be causal, with wealth affecting the EN rate a worker faces. We showed that making an EN transition feeds back into wealth, as workers who leave employment see large – roughly 70-80% – declines in their wealth, which can even persist for six years. We additionally show suggestive evidence that the elevated EN rate of low wealth workers is due to higher layoff risk, while the elevated rate of high wealth workers is due to higher voluntary quit rates. However, as our investigation of which of the types of switches drive the main result runs into limits of objective data limitations, in the next section we set up a model that we will use as a measurement device, trying to understand which features of the model economy drive the U-shape pattern that the model will replicate.

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.[11] 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:

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

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 $\lambda(\delta)$.

[11] 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.

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

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

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 interpret this rate as the fact that workers must give notice before quitting, for example having to work for a final month.[12]

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, $\lambda(\delta_l)$.

[12] 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 7: 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.

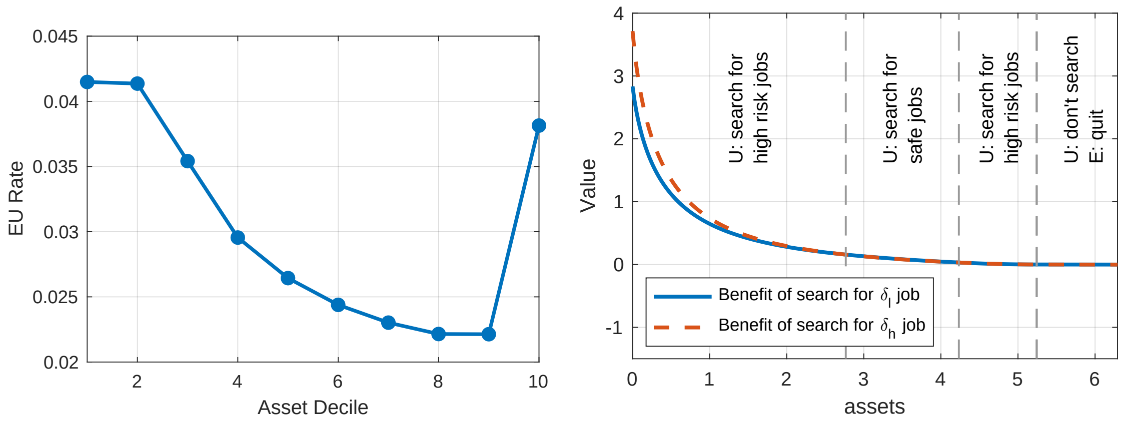
We set the parameters of the risky job and the cost of working to match our new fact that the EN-wealth relationship is U-shaped. The results in Figure 1(a) show that the ratio of the EN rate in the bottom decile (0-10%) of the wealth distribution to the rate in the fifth decile (40-50%) of the distribution 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.

Similarly, the results in Figure 1(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 7. 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

Figure 4: 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.

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 4(a), where we plot the EN rate by wealth decile in our estimated model. We replicate well the data from Figure 1, 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 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:

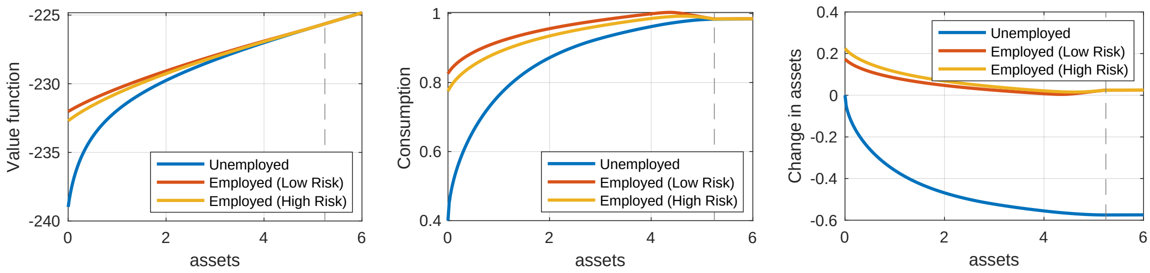
$$\lambda(\delta_h)(v^e(a,\delta_h) - v^u(a)) > \lambda(\delta_l)(v^e(a,\delta_l) - v^u(a)), \tag{7}$$

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.

Figure 5: 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).

Indeed, non-employed workers with different asset levels will prefer to search for different jobs. In Figure 4(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 job.[13] This can be seen in panels (a) and (b) of Figure 5, 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 4(b).

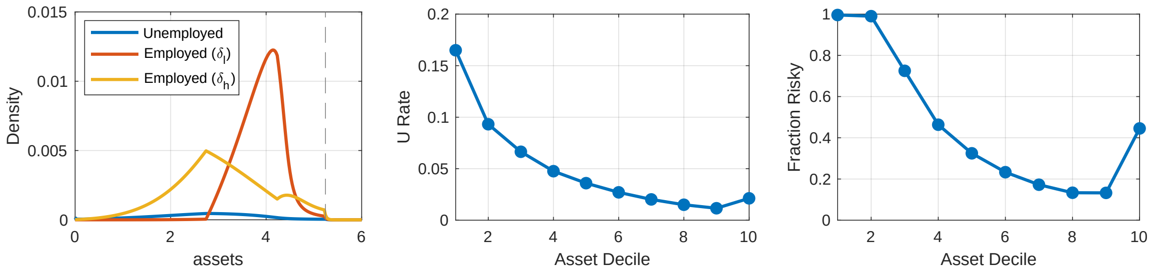
Surprisingly, despite saving them only three weeks of expected time in non-employment, low-wealth workers prefer to search for the risky job, because the consumption drop from being non-employed at low-wealth is so severe. Notice that this means that our model is also endogenously consistent with the 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.[14] 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.

[13] 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.

[14] 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 6: 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.

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 4(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 5(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 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.

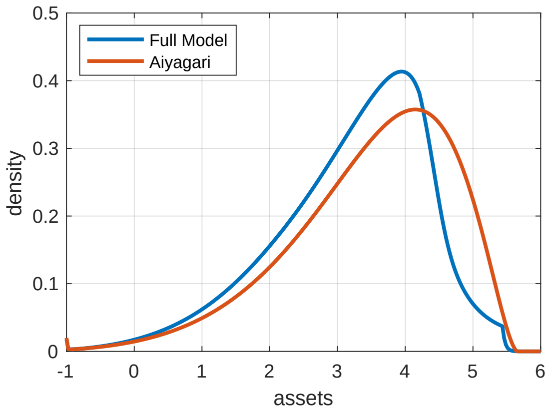
4.5 Result 2: Effect of EN switch on future wealth

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 5(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 5(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-

Figure 7: 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.

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 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.

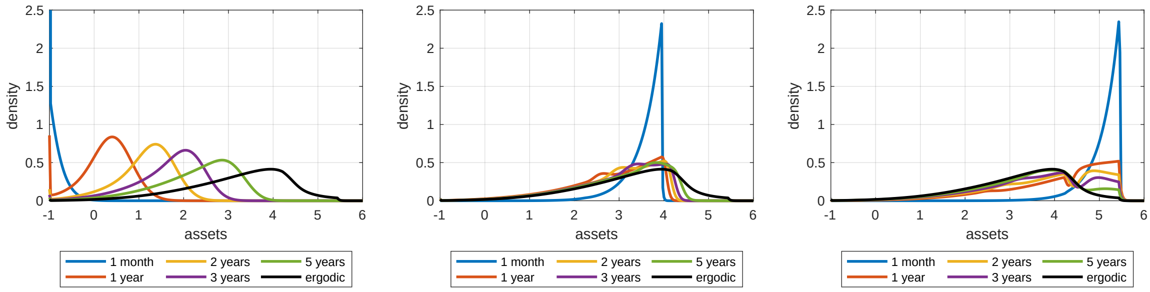
Finally, in Figure 6 we plot the equilibrium asset distribution in the model, as well as the unemployment rate and fraction of employed workers in risky jobs at each wealth decile.

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 7. 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

Figure 8: 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.

saving in the benchmark model as all agents face the same EN rate of 3% per month and NE rate of 47% per month.

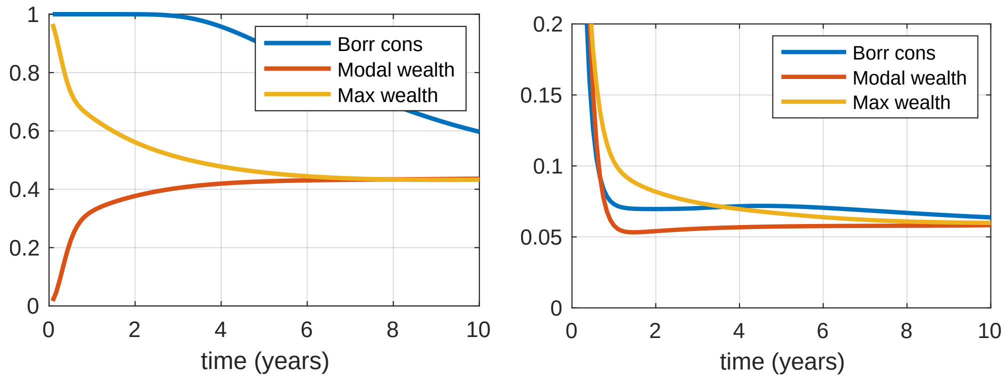
In our model, workers in safe jobs face lower exogenous job destruction rate of 2% and hence have lower precautionary savings motive. At the same time, these workers make it to the top of the wealth distribution more often as they have more time to save in employment than agents in risky jobs. The workers 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 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 8. 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.

Figure 9: 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.

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 9 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 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 Sample construction and 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
Wealth and Wage			**Occupation**		
Hourly Wage	21.41	29.19	Managerial & Professional	0.30	0.46
Wealth without home equity	103,188.10	425,198.06	Technical, Sales & Admin	0.33	0.47
Wealth with home equity	161,814.57	478,791.60	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.

Table A.2: Wealth/Wage Summary

	Wealth without Home Equity				Wealth with Home Equity			
	Wealth		**Wages**		**Wealth**		**Wages**	
	Mean	*Std.Dev*	*Mean*	*Std.Dev*	*Mean*	*Std.Dev*	*Mean*	*Std.Dev*
Decile (by wealth)								
1	-46,447.08	76,304.43	20.87	15.79	-4,2134.68	76,091.32	19.23	20.42
2	-3842.06	3,234.18	14.82	22.62	-876.42	2,195.40	12.26	17.77
3	1,733.68	1,030.14	12.27	14.21	5,757.64	2,410.66	13.40	20.04
4	6,058.97	1,564.32	14.90	18.10	16,639.43	3,864.41	15.29	18.00
5	12,454.95	2,218.83	16.89	18.62	33,439.82	5,895.34	16.93	10.54
6	22,055.34	3,540.29	19.29	20.28	59,297.70	9,007.25	18.62	14.06
7	39,200.07	6,790.25	20.70	14.81	96,986.07	13,343.30	21.32	19.74
8	75,294.86	15,005.36	23.39	18.30	160,179.54	23,730.47	24.13	19.17
9	164,469.64	41,527.38	28.08	24.89	290,637.41	57,941.61	29.02	28.77
10	809,223.83	1,249,643.33	41.69	67.34	1,054,857.83	1,307,915.15	42.63	65.86
Total	108,808.43	465,004.82	21.39	29.07	168,695.46	519,614.93	21.39	29.07

Note: 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 after implementing sample restrictions.

A.2 Alternative Estimators

In this section we re-estimate Equation (2) taking the transformation Φ to be either logistic or linear. The results are presented in Tables A.3 and A.4. While the predicted effects of being in each of the tail of the wealth distribution on the probability of experiencing an EN transition differ slightly from those obtained in the probit specification, overall we uncover the same U-shaped pattern.

Table A.3: Focusing on the 10%-Tails of the Wealth Distribution: logit model.

	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
Bottom 10	0.338***	0.046***	0.318***	0.036***	0.332***	0.037***	0.506***	0.072***	0.366***	0.042***	0.376***	0.043***
	(0.070)		(0.074)		(0.075)		(0.066)		(0.070)		(0.070)	
Top 10	-0.523***	-0.052***	0.285***	0.032***	0.270***	0.029***	-0.566***	-0.054***	0.240**	0.026**	0.215**	0.023**
	(0.089)		(0.100)		(0.100)		(0.093)		(0.107)		(0.107)	
Observations	20604		19128		19051		20604		19128		19051	
Individuals	5008		4835		4830		5008		4835		4830	
Pseudo R^2	0.007		0.076		0.083		0.010		0.076		0.084	
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. Base group is the middle of the distribution. Individual controls include age, education, female, race, married, children, region and year. Columns (1)-(3) consider wealth bins without home equity, in columns (4)-(6) wealth bins are worked out with the inclusion of home equity.

Table A.4: Focusing on the 10%-Tails of the Wealth Distribution: LPM model.

	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
Bottom 10	0.046***	0.046***	0.037***	0.037***	0.039***	0.039***	0.071***	0.071***	0.048***	0.048***	0.048***	0.048***
	(0.010)		(0.010)		(0.010)		(0.011)		(0.010)		(0.010)	
Top 10	-0.052***	-0.052***	0.038***	0.038***	0.035***	0.035***	-0.055***	-0.055***	0.034***	0.034***	0.030***	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	
Pseudo R^2												
Individual Controls	No		Yes		Yes		No		Yes		Yes	
Industry/Occupation	No		No		Yes		No		No		Yes	

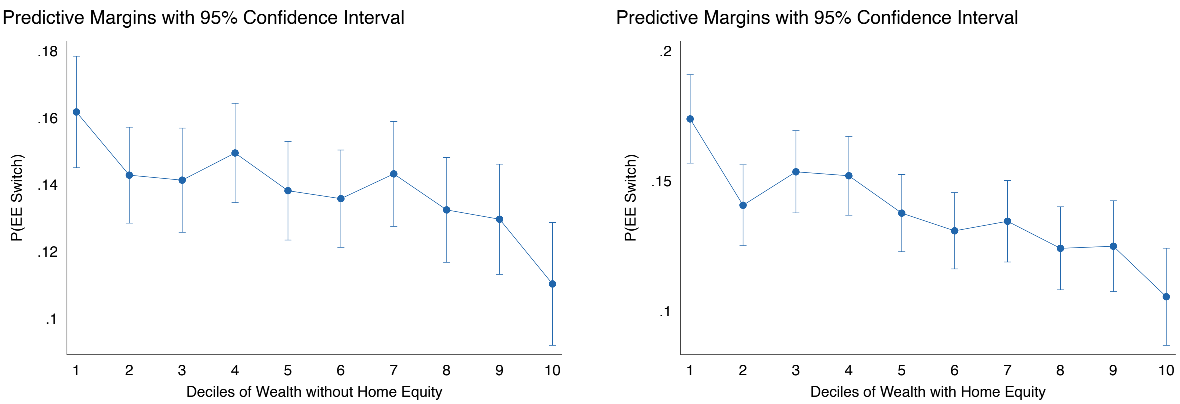
* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Note: Standard errors are clustered at the individual level. Base group is the middle of the distribution. Individual controls include age, education, female, race, married, children, region and year. Columns (1)-(3) consider wealth bins without home equity, in columns (4)-(6) wealth bins are worked out with the inclusion of home equity.

A.3 Job to Job (EE) Switches

In this section we present evidence that the effect of wealth on EN transitions is both qualitatively and quantitatively different from the effect of wealth on EE transitions. Figure A.1 presents the results of an exercise analogous to that presented on Figure 1 in the main body of the paper. 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 A.1: Margins of Deciles of wealth on the probability of an EE-Switch or Any-Switch type



(a) (b)

Note: These figures plot the predictive margins on deciles of wealth from a regression as presented in equation 1. Panels A.1b and A.1a are plotting the probability of an EE-switch, both with and without home equity respectively.

Next, we conduct a more formal test, focussing on the tails of the wealth distribution, similarly to those reported in Table 2 in the main body of the paper. The results of this exercise are reported in Table A.5. There is strong and robust evidence of the likelihood of EE transitions decline in wealth.

Table A.5: Focusing on the 10%-Tails of the Wealth Distribution: EE Transitions.

	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
Bottom 10	0.196***	0.044***	0.085**	0.016**	0.090**	0.017**	0.280***	0.064***	0.146***	0.029***	0.148***	0.029***
	(0.038)		(0.041)		(0.041)		(0.037)		(0.040)		(0.041)	
Top 10	-0.415***	-0.064***	-0.206***	-0.033***	-0.211***	-0.033***	-0.443***	-0.066***	-0.241***	-0.038***	-0.246***	-0.038***
	(0.052)		(0.058)		(0.059)		(0.054)		(0.061)		(0.060)	
Observations	20604		19128		19048		20604		19128		19048	
Individuals	5008		4835		4830		5008		4835		4830	
Pseudo R^2	0.016		0.058		0.064		0.019		0.059		0.065	
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. Base group is the middle of the distribution. Individual controls include age, education, female, race, married, children, region and year. Columns (1)-(3) consider wealth bins without home equity, in columns (4)-(6) wealth bins are worked out with the inclusion of home equity.

A.4 Further Lifecycle Results

We investigate the robustness of the U-shaped pattern to age more formally in Table A.6. We split our sample to consider three different age groups: $18-34$, $35-49$ and $50-65$. For low

Table A.6: Focusing on the 10%-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	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Bottom 10	0.206***	0.055***	0.119	0.021	0.276**	0.049**	0.235***	0.064***	0.169**	0.031**	0.230	0.041
	(0.053)		(0.077)		(0.126)		(0.049)		(0.076)		(0.158)	
Top 10	0.261**	0.072**	0.135	0.024	-0.027	-0.004	0.279**	0.077**	0.135	0.024	-0.150	-0.021
	(0.113)		(0.082)		(0.084)		(0.128)		(0.083)		(0.092)	
Observations	7902		7086		4056		7902		7086		4056	
Individuals	2900		2387		1297		2900		2387		1297	
Pseudo R^2	0.088		0.064		0.052		0.089		0.065		0.053	
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. Base group is the middle of the distribution. Individual controls include age, education, female, race, married, children, region and year. Columns (1)-(3) consider wealth bins without home equity, in columns (4)-(6) wealth bins are worked out with the inclusion of home equity.

wealth agents, the high EN risk persists well into middle age, with column (1) and (4) and (5) showing a highly positive and statistically significant marginal effect of low wealth compared to the middle, these agents around 3 percentage points to 6 percentage points more likely to experience an EN risk compared to the rest of the distribution. Turning our attention the high wealth agents, they are more likely to experience an EN-switch and the difference is largest for the younger agents (more than 7 percentage points) dropping to approximately 2.5 percentage points for middle aged individuals.