Heterogeneous Procyclicality in Earnings Growth

Labor Market Dynamics along the Income Distribution

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November 4, 2021

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Abstract

Earnings growth is more procyclical at the bottom of the income distribution than at the top. I show that the main

I show that the main driver behind this phenomenon is a larger impact of job-finding at the bottom. To assess the welfare effects of this heterogeneity, I present a model featuring endogenous job-search and incomplete insurance.

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1 Introduction

Earnings at the low end of the income distribution are more correlated with aggregate earnings growth Guvenen et al. (2017). I show that the heterogeneity in procyclicality is due to extensive margin transitions, and specifically job-finding. To investigate the welfare consequences of this phenomenon, I propose a heterogeneous agent business-cycle model that generates heterogeneous procyclicality in earnings growth driven by job-finding. I use this model to evaluate three policies aimed at reducing business cycle risk: countercyclical hiring subsidies, countercyclical unemployment benefits and universal basic income (UBI). I find that, in the model, hiring subsidies and countercyclical benefits increase welfare. Universal basic income decreases earnings cyclicality but lowers welfare overall.

Using administrative microdata from Germany, I regress quantile-specific yearly earnings growth on aggregate growth to estimate so called "earnings betas", along the income distribution, similar to Guvenen et al. (2017). Corroborating their findings in US data, I find that the estimated coefficients in Germany slope sharply downwards along the distribution: as aggregate earnings growth increases by 1 percent, earnings for individuals in the lowest decile rise by more than 3 percent, while they rise by less than 1 percent for the top decile. My main contribution to the literature is the decomposition of these earnings betas into the contributions of different labor-market transitions. First, I show that earnings at the bottom of the income distribution are more procyclical due to job-market transitions. I show this by restricting the sample to individuals who stay in the same job and re-estimating the regression coefficients. The results show that for a 1 percent increase in aggregate earnings, the earnings growth of job-stayers increases by about half as much, homogeneously along the income distribution. To investigate this further, I exclude individuals who transition from employment to unemployment, i.e. job-separators, and re-estimate the earnings betas. This exercise decreases the correlation coefficients across the distribution, but the heterogeneity remains. I infer that the contribution of job-separations to earnings cyclicality is fairly homogeneous across the distribution, and not the main force responsible for the heterogeneity in the data. In conclude that job-finding is the main reason for the strong heterogeneity in procyclicality of earnings growth along the income distribution. To my knowledge, I am the first to document this decomposition. The reason for this phenomenon is that, at the bottom of the income distribution, job-finding is low, and separations rates are high. This leads to a strong prevalence of unemployment. At the top, this pattern is reversed. Therefore, changes in job-finding probabilities over the business cycle, have a larger impact at the bottom of the income distribution.

The second part of the paper presents a standard macroeconomic model featuring business cycle risk and a frictional labor market, aiming to evaluate labor market policies which address the heterogeneous exposure of earnings to the business cycle. The model features heterogeneous, risk-averse workers who search for jobs across submarkets which differ in offered wages and job-finding probabilities. Workers differ along three dimensions: productivity, wealth and wages. When deciding where to search for jobs, they endogenously trade off higher job-finding probabilities for higher wages. Hence, in the model, both worker choices and job-supply risk influence earnings growth. Agents can smooth consumption and insure against earnings risk by saving in a risk free asset.

During an employment spell, workers receive a wage which is fixed for the duration of the spell. In unemployment, they receive unemployment benefits and produce a value of home production. In this setup, highly productive workers have strong incentives to find work quickly, for two reasons. First, their potential market wages substantially exceed their income in unemployment, i.e. they are missing out on potential earnings. Second, workers can insure against a fall in their productivity by entering a match, as the wage is fixed for the duration of the match. Workers achieve this by searching in submarkets which offer relatively low wages, relative to productivity. On the other hand, low productivity workers have high reservation wages, relative to their productivity, because for them the income from home production has meaningful impact. This leads them to search in submarkets which offer low job-finding probabilities. These forces endogenously create heterogeneous job-finding probabilities along the income distribution, which is a key feature of the data. I calibrate the model to match key moments of the German labor market, including heterogeneous job-market transition rates, but leave earnings growth and cyclicality untargeted.

I solve for the model's response to a series of aggregate productivity shocks. It is able to reproduce the strongly decreasing procyclicality of earnings growth, as well as the heterogeneous contribution of job-finding, along the income distribution. The main driver behind this finding, as in the data, is the higher prevalence of non-employment at the low end of the income distribution.

I apply the model in the evaluation of three labor market policies which have the potential to reduce labor market risk. I quantify the welfare impact of these policies in two ways: first, I solve for aggregate welfare in the model economy in the first period after the arrival of an unexpected negative shock to aggregate productivity and compare it to the baseline economy; second, I estimate the cyclicality of aggregate consumption.

The first policy is a countercyclical hiring subsidy, aimed at reducing the risk of lower vacancy posting, disproportionately borne by low-productivity workers. In this counterfactual, firms receive a one-time lump-sum transfer from the government when a match is formed, with the size of the subsidy indexed to aggregate productivity. In case of a negative productivity shock of 1 percent, the subsidy offsets the vacancy posting cost. After an unexpected shock to aggregate productivity, compared to the baseline economy, welfare in the economy with a countercyclical hiring subsidy is increased. The reason is that vacancy creation does not fall as much as in the baseline case, enabling workers to find matches at higher rates. This decreases risk in the economy and the variance of aggregate consumption falls.

Second, I introduce countercyclical unemployment benefits, aimed at helping agents smooth consumption over the business cycle. Such a policy is in place in many US states. Since the model does not incorporate the time-limited benefit structure of the German unemployment insurance system, an increase in benefits could also be interpreted as a benefit extension. The size of the benefit increase is indexed such that the cost of this policy is similar to cost of the hiring subsidy. I find that countercyclical unemployment benefits slightly decrease welfare, as measured in the initial period after a negative productivity shock. The reason is that the moral hazard cost in the model is high: when receiving higher unemployment benefits in recessions, workers search in higher wage-submarkets, which offer lower job-finding probabilities. The result is more cyclical aggregate consumption. To quantify the moral hazard effect of unemployment benefits in my model, I show that, in steady state, increasing unemployment benefits has a positive effect on welfare if worker choices are fixed, implying that there is positive insurance value. However, if workers can adjust their search decisions, welfare falls, as they stay unemployed longer, imposing a higher fiscal cost on all workers.

The third policy experiment eliminates unemployment benefits and in its stead introduces a UBI into the economy. The size of the payment is calibrated such that it is financed with the same steady state tax liability as the unemployment benefits in the baseline economy. I find that this policy strongly increases job-finding, as, at the lower end of the income distribution, it removes the disincentive to work caused by unemployment benefits. At the top of the distribution, job-finding rises because the payments received in unemployment are lower than those under the baseline system with benefits indexed to productivity. I find that UBI decreases the cyclicality of earnings and consumption along the business cycle. However, welfare is lower compared to the baseline economy, as the insurance value of the unconditional payments is very low, forcing workers to self-insure more than they would in the baseline economy. Furthermore, there is considerably less redistribution under the UBI system, compared to a system with unemployment benefits.

Related Literature The empirical part of this paper is related to a fast growing literature documenting how earnings growth rates change over the business cycle.[1] Storesletten et al. (2004) find that earnings risk is highly countercyclical in the US, as measured by the variance of earnings growth. Using administrative tax data Guvenen et al. (2014) find that, while the variance of earnings growth rates is acyclical, higher order moments such as skewness and kurtosis are cyclical, as well as heterogeneous across the income distribution. Similar results have been found for other countries, such as Germany, France and Sweden (Busch et al., 2018), Denmark (Harmenberg and Sievertsen, 2017), as well as Italy (Hoffmann and Malacrino, 2019). Pruitt and Turner (2020), find evidence that in the US, intra-family insurance and added worker effects lead to less procyclical earnings growth skewness within households, compared to singles. Relatedly, Guvenen et al. (2017) and Dany-Knedlik et al. (2021) show that in the US, "earnings betas", i.e. the correlation between individual and aggregate earnings growth, are higher at the bottom of the income distribution. I extend these analyses by separately studying the cyclicality of earnings growth rates and labor market transitions in the context of Germany. Similar to previous research I find that earnings growth is more cyclical towards the bottom of the income distribution. Crucially, I show that a large part of heterogeneous earnings growth cyclicality can be explained by heterogeneous extensive margin transition probabilities.

Further, this paper is related to a literature seeking to account for the empirical regularities in earnings processes outlined above using theoretical models. Hubmer (2018) shows that a job-ladder model with savings, risk aversion, skill depreciation in unemployment and endogenous search effort can account for the stylized facts documented by Guvenen et al. (2015). Similarly, Karahan et al. (2019) document heterogeneous labor market transition patterns across the lifetime earnings distribution. They also show that a model with ex-ante worker heterogeneity in learning ability and job ladder risk can account for them. Harmenberg and Sievertsen (2017) shows that a job-ladder model can replicates the procyclical skewness in Danish earnings growth data. To my knowledge, this paper features the first model which replicates heterogeneous earnings betas along the earnings distribution. Furthermore, the model is able to generate countercyclical and heterogeneneous separation probabilities, which are typically assumed to be constant in the literature.[2]

The model presented in this paper is a directed search model similar to the one presented

[1] A related literature studies earnings growth heterogeneity without a focus on cyclicality (see De Nardi et al., 2021; Guvenen et al., 2014; Halvorsen et al., 2019). Similarly, there is a growing literature showing heterogeneous incidence of monetary policy along the earnings distribution (see Broer et al., 2020; Holm et al., 2020)

[2] Mueller (2017) finds that separations are countercyclical in the US, but more so at the top.

in Chaumont and Shi (2018), but featuring idiosyncratic worker-level productivity shocks. The model allows for tractability, even in the presence of borrowing constraints, labor market search and unemployment risk due to a feature referred to as a block recursive equilibrium (Menzio and Shi, 2010). In these models, the policy functions of firms and consumers can be solved for separately from the distribution of workers in equilibrium. Chaumont and Shi (2018) use their model to show that directed search models that feature precautionary savings can generate more realistic wealth distributions than other models. Along similar lines, Eeckhout et al. (2020) show that the interplay between wealth and search can explain labor market sorting into differently productive jobs. Birinci and See (2019) use a directed search model to show that time-varying unemployment benefits can help smooth consumption in recessions. I add to this literature by showing that directed search models combined with idiosyncratic worker productivity can explain patterns of labor market transition rates found in the data, in steady state and along the transition path.

Finally, this paper relates to a long literature investigating policies which stabilize the macroeconomy during a recession (see, e.g., McKay and Reis, 2016) and on the optimal cyclicality of unemployment benefits (Birinci and See, 2019; Mitman and Rabinovich, 2015). Similar to their work, I evaluate the welfare effects of an increase in unemployment benefits during a downturn. I also evaluate the effectiveness of hiring subsidies. Kitao et al. (2011) show that this instrument can be particularly powerful in weaker labor markets.

The rest of the paper is organized as follows. Section 2 presents the empirical analysis of the paper. Section 3 outlines the model and the calibration. Section 5 presents the model results. Section 6 discusses the policy experiments and section 7 concludes.

2 Empirical Analysis

The empirical analysis in this paper is inspired by Guvenen et al. (2017). Using administrative social security data, they estimate individuals' exposure to the business cycle by estimating what they term "earnings betas" across the earnings distribution. The approach, inspired by the Capital Asset Pricing Model (CAPM), regresses individual earnings growth, within a section of the permanent income distribution, on aggregate earnings growth as follows:

$$\Delta y_{i,t} = \alpha_q + \beta_q \Delta Y_t + \epsilon_{i,t}$$

They find that the regression coefficient β_q is about three times larger at the bottom of the income distribution, compared to the top, i.e. a 1% increase in aggregate earnings growth leads to a 3% increase in individual earnings growth at the bottom of the distribution, but only a 1% increase towards the top.

In this section, I extend their analysis by decomposing the earnings betas into the contributions by different labor market transitions in order to pinpoint the drivers of the heterogeneity. For the case of Germany, I first document that, like in the US, earnings growth towards the bottom of the income distribution is considerably more procyclical compared to the top. The magnitudes in the regression coefficients are very similar across the two countries. To investigate the causes of the heterogeneity, I investigate the earnings betas across multiple subsamples of labor market transitions.

When restricting the sample to job-stayers, i.e. excluding the extensive margin, procyclicality is homogeneous across the distribution and earnings growth moves less than one-for-one with the aggregate. Along the extensive margin, I then identify the contributions of job-finding and separations. Excluding separations reduces the procyclicality of earnings growth, but homogeneously so. Excluding job-finders from the sample, however, reduces the regression coefficients β_q at the bottom of the distribution considerably, implying that this transition is responsible for most of the observed heterogeneity.

2.1 Data

For the empirical exercise, I utilize the Sample of Integrated Labor Market Biographies (SIAB), constructed by the Research Data Center (FDZ) of the German Federal Employment Agency (BA). It contains administrative data on a representative two percent sample of German labor market histories between 1975 and 2014, with the exception of civil servants, students and self-employed individuals.[3]

The dataset is divided into labor market spells, which mark distinct episodes during an individuals labor market biography. For each such spell, the data provides information about its start- and end-date, as well as average daily earnings throughout its duration. Since firms are required to notify the responsible social security agencies about their employees at least once per year (Ganzer et al., 2017), the maximum spell length is one year.

For employed individuals, the earnings measure is pre-tax earnings liable to social security contributions; for non-employed individuals, some unemployment benefit receipts are reported.[4] The dataset does not report spells of periods of non-employment without benefit receipts.[5] To construct complete labor market biographies, I declare any missing values at any point during an individuals life as non-employment episodes, except for those before their first or after their last non-missing episode in the data.[6]

I deflate all earnings using the quarterly consumer price index.[7] For the subset of non-employed individuals who receive unemployment benefits (henceforth referred to as the unemployed), I also observe benefit income. However, since the duration and generosity of unemployment benefits changed throughout the sample, the series is not consistent over time. Hence, in the baseline estimation, earnings of all non-employed individuals are set to zero. In the appendix, I perform a robustness exercise including Unemployment Benefits I as an income measure for the unemployed.

I convert average daily earnings during labor market spells to quarterly earnings. To obtain binary quarterly employment status, I assign individuals who are employed for more than half of a quarter into employment and all others into non-employment. Employed

[3]The excluded individuals make up around 20% of the workforce (Busch et al., 2018).

[4] Several forms of unemployment benefits are reported: i) Unemployment Benefits I (*Arbeitslosengeld I*), which represent an earnings replacement payment immediately after job-loss, for a limited time, (ii) Unemployment Help (*Arbeitslosenhilfe*) benefits claimable after exhaustion of unemployment benefits, (iii) Unemployment Benefits II (*Arbeitslosengeld II*), the successor of the Unemployment Help program, implemented through the Agenda 2010 program in 2005. There is no data on Unemployment Benefits II between the years of 2004 and 2007.

[5]For the latter years of the sample period, the data also contains information on job-search and marginal part-time employment. To keep the sample consistent over time, individuals in these categories are assigned to non-employment.

[6]For individuals younger than 60 years, I also declare as non-employed all episodes after their last employment observation if that observation falls into the years 2013 and 2014. The number of non-employed individuals would fall drastically towards the end of the sample otherwise.

[7]The CPI index (base year 2015) is obtained from the Federal Reserve Bank of Saint Louis' FRED database, and is not seasonally adjusted. The variable ID is DEUCPIALLQINMEI.

individuals are assigned the average earnings value of the longest employment spell during the quarter.[8]

Because social security contributions are capped at the assessment ceiling for pension insurance, the earnings data are censored from above, affecting around 6 % of the total observations. In most of the empirical analysis that follows, I focus on the lower 90% of the earnings distribution but impute top-earnings following Card et al. (2013) and Dustmann et al. (2009). Their approach relies on predicting the censored observations using a Tobit estimation.[9] Note that because the imputed earnings are randomly drawn from estimated distributions, the earnings growth they produce for each individual is not informative and the earnings growth rates among the top 10 percent should be interpreted with this in mind.

To make the data consistent over time, first, I exclude individuals employed in the states of the former German Democratic Republic. Second, marginal part time workers are declared as non-employed since they are only registered in the dataset after 1999 and are previously unobserved. Third, due to large fluctuations in the number of individuals whose employment status is coded as "Other employment status" (Ganzer et al., 2017), I label all of these as non-employed in all years of the sample. For my analysis, I restrict the sample period to 1980-2014 and to individuals older than 25 years and younger than 60, leaving close to 70 million person-quarter observations.

2.2 Descriptive Statistics

For each quarter, I generate an income distribution by sorting individuals according to their recent earnings, following Guvenen et al. (2014). Recent earnings are constructed by averaging individual quarterly labor earnings (including zeros) over five years prior to quarter t.[10] This measure is intended as a proxy for permanent income (results are similar using lifetime earnings as a sorting variable) and individuals are split into 20 quantiles along its distribution, trading off noise reduction (larger quantiles) and granularity (smaller quantiles). I exclude individuals who do not receive any labor earnings during the five year period. Furthermore, because age and gender are influential predictors of recent earnings, I construct the quantiles outlined above conditional on these characteristics, by assigning individuals to 5-year age brackets.

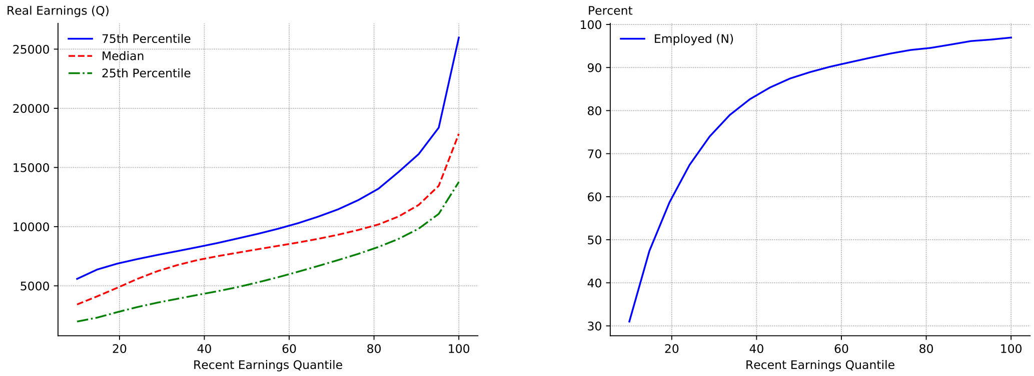
The left panel of Figure 1 shows the median of real quarterly earnings in quarter t, as well as the 25th and 75th percentile, conditional on employment. Median labor earnings are about three times larger at the top, compared to the bottom. Interestingly, the slope of the earnings curve starts out relatively steep, but flattens out around the median of the recent earnings distribution, steepening again towards the top.

[8] Note that individuals who are non-employed for less than a full quarter and employed for the rest are declared to be employed. Employment spells that are longer than one quarter are split into multiple quarters. The earnings for each quarter are the earnings of the overarching spell.

[9] A second approach fits a Pareto distribution to the upper tail of the earnings distribution and draws replacements for the censored earnigns observations using this method. Dustmann et al. (2009) conclude, drawing on a separate dataset, that the Tobit approach is preferable. In the context of my exercise, results are very similar.

[10] As a robustness exercise, I construct a recent earnings distribution excluding zeros in the appendix and perform the same estimations as in the baseline. Results are very similar.

Figure 1: Earnings and Employment across the distribution



(a) Real Earnings (b) Employment status

Note: The *Left Panel* shows the median, 25th and 75th percentile of real gross quarterly earnings by quantile, deflated using the CPI with base year 2005. The *Right Panel* shows the average employment share by quantile. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

The right panel of Figure 1 plots the share of employed individuals across the distribution. While only close to 30 % of individuals in the first quantile are employed according to the definition outlined above, the fraction rises to 80 % at the 4th decile and to above 90 % beyond the median.

Next, I compute average earnings growth by quantile. Here, I make a crucial modification to the approach used by Guvenen et al. (2017): I include the extensive margin of labor market transitions. I average real earnings by quantile (including zeros) and compute the growth of this measure over time (Krueger et al., 2016):

$$\Delta \overline{y}^q_{t,k} = \log(\overline{y}^q_{t+k}) - \log(\overline{y}^q_t) \tag{1}$$

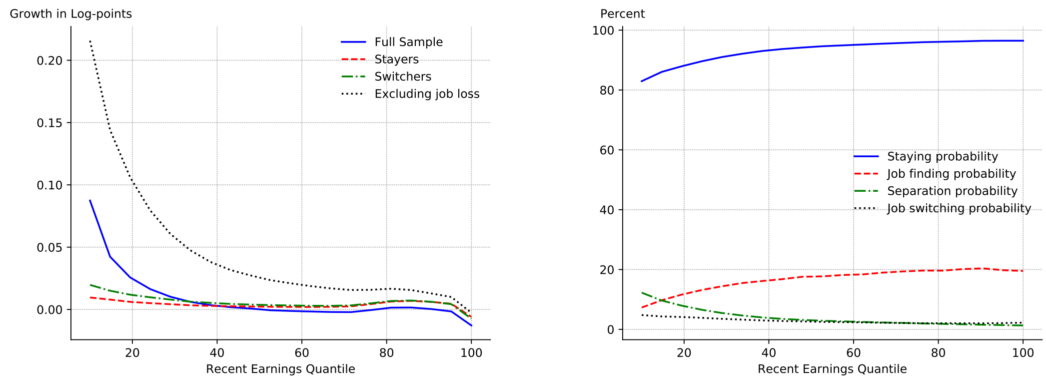
$$\text{where } \overline{y}^q_{t+k} = \frac{1}{N_q}\sum_i y_{i,t+k} \quad \forall i \in q$$

where $\overline{y}^q_{t+k}$ represents average earnings in quarter $t+k$, for all individuals who are in quantile q in period t and consequently, $\Delta\overline{y}^q_t$ is the log-growth of average earnings. This approach has the advantage of being able to include zeros in a log-growth rate, as they are subsumed in the aggregate. Using individual growth rates, this is not possible.

Furthermore, my dataset allows my to compute earnings growth rates separately by labor market transitions. I consider five such transitions: job-stayers are individuals who remain with the same employer between periods t and $t+k$, job-switchers are individuals who are employed in periods t and $t+k$, but with different employers, job losers are individuals who are employed in quarter t but non-employed in period $t+k$, job finders are non-employed in period t and employed in period $t+k$ and finally, all other individuals are non-employed in both periods t and $t+k$. In what follows, I decompose average earnings growth over time along these dimensions.

The red line in the left panel of Figure 2 displays quarterly earnings growth (k=1) across the earnings distribution. While earnings growth, is as high as 10 % in the first quantile, it turns negative around the median, indicating mean reversion over time. First, I exclude all individuals who transition from employment to non-employment between quarters t and $t+1$ (blue line). This removes all downside risk for the employed, but retains upside potential for the non-employed. Unsurprisingly, earnings growth for this restricted sample is considerably higher, especially at the bottom, increasing growth by more than 0.1 log-points. At the top of the distribution, growth only increases by around 0.02 log-points when separators are excluded.

Figure 2: Earnings growth and Transitions across the distribution



(a) Earnings growth (b) Transition probabilities

Note: The *Left Panel* shows average earnings growth between t and $t+1$ for various sub-samples, calculated according to Equation (1), by quantile. The blue line represents average earnings growth for the full sample, the black line excludes job-losers, the green line limits the sample to those who are employed in periods t and $t+1$, the red line only includes job-stayers. The *Right Panel* shows the average transition probabilities between employment states. The blue line represents the probability of staying employed, the red line represents job-finding probability, the green line the probability of separation and the black line the probability of switching employers. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

Next, I remove all extensive-margin transitions, by restricting the sample to those who are employed in period t and $t+1$. This almost perfectly equalizes average earnings growth across the distribution, with now only slightly higher growth towards the bottom end of the distribution. Restricting the sample even further, to only include individuals who stay with the same employer, shows that the slightly higher growth rate at the bottom seems to be mainly driven by job-switchers.

Focusing more explicitly on labor market transitions, the right panel of Figure 2 shows quarterly transition probabilities across the distribution. Focusing on the initially employed, there is a striking difference in separation probabilities between the bottom and the top of the earnings distribution: while the employed in the first quantiles face a 30 % chance of transitioning into non-employment, the probability is almost zero at the very top. Furthermore, while generally low, the job-switching probability is higher at the bottom as well. Shifting to the non-employed, the figure shows a strong upward slope in quarterly job-finding probabilities across the distribution, implying longer unemployment duration at the bottom. These forces cause the strong heterogeneity in employment status documented in the right panel of figure 1.

2.3 Earnings procyclicality across the distribution

Next, I document heterogeneity in the procyclicality of earnings by quantile, similar to Guvenen et al. (2017). I regress the measure of earnings growth introduced in Equation (1) on aggregate earnings growth, by quantile. As measure for aggregate growth, I choose growth in average earnings constructed analogously to the quantile-specific growth measure:

$$\Delta Y_{t,k}^{earn} = \log(\overline{y}_{t+k}) - \log(\overline{y}_t)$$
$$\text{where } \overline{y}_{t+k} = \frac{1}{N}\sum_i y_{i,t+k}$$

Using the growth rates constructed in this way, the procyclicality of earnings along the income distribution can be estimated using the following regression:

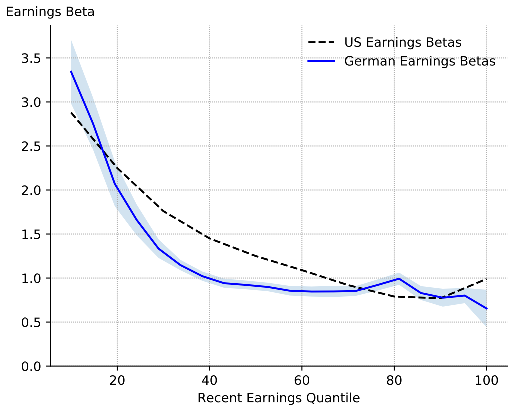
$$\Delta \overline{y}_{t,k}^{q} = \alpha + \beta_{Y,k}^{q} \Delta Y_{t,k} + X_t + \epsilon_{q,t} \tag{2}$$

where β_Y^q represents the change in quantile-specific growth in response to a 1 percentage point increase in aggregate growth and X_t contains calendar-quarter dummies to account for seasonality. For this analysis, I focus on yearly quarter-on-quarter growth rates, implying $k = 4$.

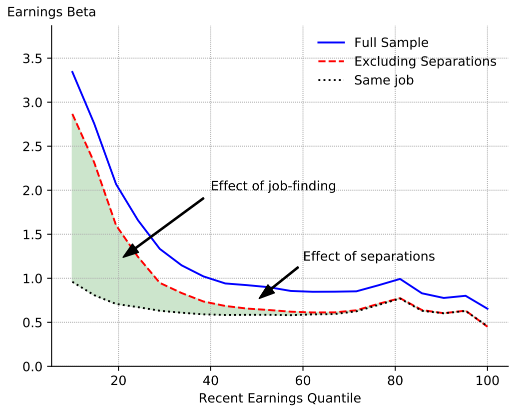
The left panel of Figure 3 plots the values of $\beta_{Y,4}^q$ obtained from Equation (2) across the earnings distribution. Individuals at the bottom of the distribution see their earnings growth rise by more than 3 percentage points, on average, for every additional percentage point in aggregate earnings growth. The same relationship is less than 1-for-1 beyond the 40th percentile, but increasing slightly again between deciles seven and eight. Beyond the 80th percentile, the graph shows a decrease in the earnings betas, likely driven by the imputation of top incomes.

These results are strikingly similar to the ones documented by Guvenen et al. (2015) for the case of the US. The black dashed line in the top-left panel of Figure 3 reports the earnings betas for males, aged 36-45, as reported in the online appendix Table B1 in Guvenen et al. (2015). Importantly, they conduct their analysis using annual earnings growth rates. Still, in both countries, earnings growth is about three times as procyclical at the bottom of the income distribution as it is at the top. The slope is steeper in Germany, implying that around the median, earnings growth is more procyclical in the US.

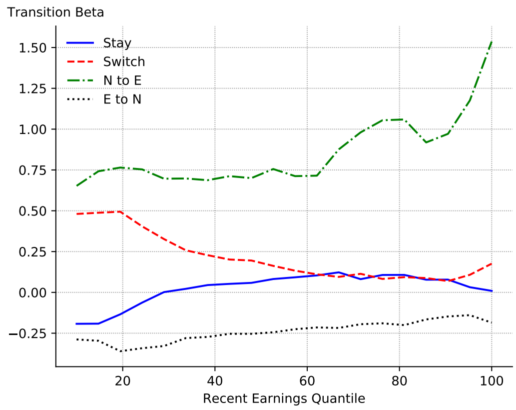
Figure 3: Cyclicality of Earnings Growth



(a) Earnings Beta



(b) Earnings beta, subsample



(c) Cyclicality of transition probabilities

Note: The *Left Panel* plots the coefficients $\beta^q_{Y,k}$ from equation (2) (blue), by quantile. The dashed black line reproduces the GDP earnings beta for men aged 36-45, as reported by Guvenen et al. (2017). The *Right Panel* shows the estimates for the coefficient $\beta^q_{Y,k}$ from Equation (2) for two additional subsamples. The blue line utilizes the full sample, the red, dashed line excludes individuals who are employed in quarter t and non-employed in quarter $t+4$, the black, dotted line restricts the sample to those employed in both periods t and $t+4$. The area between the solid and dashed lines represents the change in the beta-coefficients upon the exclusion of individuals who separate. The shaded region marks the contribution of job-finding to the beta-coefficients. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

In order to investigate possible reasons for the stark heterogeneity in the procyclicality of earnings growth rates across the distribution, I proceed similarly to Figure 2, by restricting the sample to subgroups and investigating the effect on the regression-coefficients in Equation (2). The right panel in Figure 3 shows the result of this exercise. When restricting the sample to individuals who stay in the same job between quarters t and $t+4$, the coefficients are close to homogeneous along the earnings distribution. Earnings are procyclical for job-stayers, but their earnings grow only half as much as aggregate earnings. I interpret the difference between the beta coefficients estimated for the full sample on the one hand and the job-stayers on the other as the contribution of the extensive margin. The graph suggests that this contribution is considerably larger towards the bottom of the distribution than it is at the top.

Decomposing the contribution of the extensive margin into those by job-finders and job-separators presents a challenge. It is not possible to compute earnings growth rates for either group, as all job-finders, by definition, have zero earnings in period t, and all separators earn zero in period $t+4$. In order to still pin down which margin is responsible for the strong heterogeneity in earnings growth rates across the distribution, I restrict the sample in steps. First, I focus on all individuals who do not transition from employment in quarter t to non-employment in quarter $t+4$ (separations) and re-estimate the regression in Equation (2). The resulting coefficients are plotted as the red, dashed line in the right panel of Figure 3b. Across the distribution, the earnings betas for this subsample are lower than they are for the full sample. The shift is almost homogeneous, with coefficients decreasing by between 0.25 and 0.5 percentage points. The contribution of separations to the overall beta-estimates, therefore, appears to be fairly similar between the bottom and the top of the recent earnings distribution. Importantly, the earnings betas estimated for the described subsample are still steeply decreasing from close to 3 in the first decile to 0.5 around the median of the income distribution.

Crucially, the beta-coefficients estimated for the above subsample also identify the contribution of job-finders to the earnings beta. In the right panel of Figure 3b, this is the shaded green area between the dotted black line, the beta-coefficients for the subsample of job-stayers, and the dashed red line, the coefficients when the estimation sample includes job-stayers and job-finders (but excludes job-separators). The striking difference between the two lines is due to the addition of job-finders. In the first decile of the recent earnings distribution, the addition of job-finders increases the beta coefficient by more than 2 points, implying that job-finders earnings growth is highly procyclical. The effect decreases towards the median and is close to zero approaching the seventh decile.

From this decomposition, I conclude that the main reason for the observed heterogeneity in the procyclicality of earnings growth rates along the income distribution is job-finding. This fact is not unexpected, as Figure 1 shows that non-employment is considerably more prevalent towards the lower end of the income distribution. It remains to be shown, however, that job-finding is procyclical at the bottom of the recent earnings distribution. To this end, similarly to Equation (2), I estimate a regression of transition probabilities on aggregate earnings:

$$\Delta\overline{trans}^q_{t,k} = \gamma + \beta^q_{Y,k,trans}\Delta Y_t + X_t + \varepsilon_t \tag{3}$$

$$\text{where } \overline{trans}^q_{t,k} = \frac{1}{N_q}\sum_i trans_{i,t+k} \forall i \in q \tag{4}$$

where $\overline{trans}^q_t$ is the fraction of all individuals in quantile q at quarter t who transition along $trans$. I focus on four transitions paths ($trans$): (i) staying with the same employer, (ii) switching to a new employer, (iii) employed to non-employed and (iv) non-employed to employed.

The bottom panel of Figure 3 plots the values of $\beta^q_{earn,4,trans}$ from Equation (3) across the recent earnings distribution. Both staying and job-switching are moderately more pro-cyclical at the low end of the distribution, compared to the top. Job-separations countercyclical everywhere, but slightly more so at the bottom. Crucially, the probability of transitioning from non-employment to employment (green line), a one percentage point increase in aggregate earnings growth leads to a 0.75 percentage point increase from the bottom of the distribution up to the 6th decile. Beyond that, the cyclicality is increasing.

Together, these results explain the heterogeneous incidence of job-finding in driving earnings procyclicality. Non-employment is considerably more common at the low end of the recent earnings distribution. This is driven by higher separation rates and lower job-finding (right panel in figure 2). In times of a rise in aggregate earnings, job-finding increases across the distribution, driving large income gains at the bottom, but almost none at the top, as there are very few non-employed workers there.

The previous section outlines that earnings are heterogeneously procyclical, an effect driven by a heterogeneous impact of job-finding along the income distribution. In order to assess the consequences of these findings for welfare and policy, it is necessary to write a model that can reproduce the effects observed in the data, while accounting for important margins of insurance like savings and unemployment benefits. The next section provides such a model.

3 Model

In order to conduct welfare analysis of policy proposals, I provide a model that mirrors the empirical earnings beta and its decomposition. The model features heterogeneous agents, in order to capture the heterogeneity documented above. Further, this framework allows the model to speak to the policy proposals' impact on inequality in earnings and wealth.

Time is discrete and infinite. The model is a directed search model in the spirit of Chaumont and Shi (2018), bringing together a unit mass of workers and a continuum of firms. Due to search frictions, it features involuntary unemployment, endogenous to the aggregate state of the economy; and due to borrowing constraints, households are unable to perfectly insure against this risk.

3.1 Environment

The consumers in the model are risk averse, receive utility from consumption and discount the future at rate β. Hence their expected utility is

$$U_t = \sum_{s=t}^{\infty} \beta^{s-t} u(c_s)$$

The utility function $u : \mathbb{R}_+ \to \mathbb{R}$ is twice differentiable, strictly increasing, strictly concave and $u'(0) = \infty$. All consumers can save in a risk-free asset a, which pays interest rate r. Borrowing is not possible.

Households can either be employed or unemployed, with the employed supplying one unit of labor inelastically and earning $(1-\tau)w$. The variable w represents the constant wage associated with their firm-worker match and τ is a labor income tax imposed by the government. The unemployed receive unemployment benefits $b(z)$, indexed by individual productivity, and produce h of home production. Consequently, consumers differ according to their asset holdings, their employment status and their productivity.

Each individual is endowed with productivity z_t, which evolves according to the Markov process

$$\log(z_t) = \rho_z \log(z_{t-1}) + \varepsilon_t$$
$$\varepsilon_t \sim N(\mu_z, \sigma_z)$$

Labor market search in the model is directed. Households, employed and unemployed, can direct their search at wage submarkets indexed by productivity and wealth. In each submarket, workers only meet firms willing to employ them the submarket-specific wage rate. Consequently, if a worker meets a (new) firm, there is no need for wage bargaining, and they start their relationship at the beginning of the subsequent period. Wages are fixed for the duration of the match. The unemployed can search every period, while the employed can only search with probability $0 < \Lambda < 1$, capturing the fact that most of their time is spent working.

Firms are owned by risk-neutral investors, maximize profits and discount the future at the risk-free interest rate. They post vacancies across wage submarkets, taking wealth and productivity of the searching workers as given. The cost of posting a vacancy is κ and there is free entry. A firm-worker match produces according to the worker's productivity z and aggregate productivity A. Existing matches separate for two possible reasons: (i) exogenously with probability $\delta(z)$, or (ii) endogenously, if the worker finds a new job.

Submarkets are indexed by wealth, in order for firms to be able to make predictions about the workers' job-finding probabilities on-the-job.[11] These affect expected match profits, which in turn influence which wage-submarket a firm enters. If submarkets were not indexed by worker wealth, firms would need to form expectations over the workers wealth level given their productivity, requiring them to know the distribution of wealth conditional on productivity. Furthermore, upon meeting, firms and workers would need to bargain over the wage, since match surpluses would differ depending on the workers' assets.[12] This would make the problem more costly to solve computationally.

If wealth was unobservable to the firm, workers in the model would have an incentive to signal their wealth to the firm (Chaumont and Shi, 2018). In equilibrium, asset-rich workers have an incentive to search for jobs in submarkets that offer higher wages at lower job-finding probabilities. Hence, they are less likely to leave their current match for a new one than wealth-poor workers. This, all else equal, is attractive to the firm. Along these lines, Chaumont and Shi (2018) argue that workers who can signal to the firm any level of wealth less than or equal to their actual holdings, will choose to signal the true value. This, in turn, implies that submarkets will be indexed by the workers wealth level.

Within each submarket, searchers and firms meet according to a matching function $M(S, V)$, where S and V represent the mass of searchers and vacancies within each submarket, respectively. The function is strictly increasing, concave in both arguments and exhibits constant returns to scale. If a vacant firm meets a worker, they form a match. The probability of a vacancy being filled can be expressed as $q(\theta) = M(S, V)/V = M(\frac{1}{\theta}, 1)$ where $\theta = \frac{V}{S}$ represents the submarket tightness. Likewise, the probability of a worker finding a match can be written as $\eta(\theta) = M(1, \theta)$. The vacancy filling probability $q(\theta)$ is decreasing in θ, while the job finding probability $\eta(\theta)$ is increasing in θ. If a vacant firm meets more than one worker, it randomly decides which one to hire. Submarkets that are not active because no worker visits them, have $\theta = 0$.

The government finances unemployment benefits and bond issuance through a tax on labor income τ. It balances its budget every period, following a budget rule, trading off fluctuations in bond issuance with tax rate changes.

A worker's state vector can be written as (L, z, x, w), where $L \in \{U, E\}$ represents her employment status, $x \in \mathcal{X} \equiv [\underline{x}, \bar{x}] \subseteq \mathbb{R}_+$ represents her beginning of period wealth,

[11]If there was no on-the-job search, implying that the probability of an endogenous quit was zero, workers' assets would not enter the firms problem. I choose to allow workers to search in order for the model to be able to match the labor market flows I observe in the data.

[12]This problem is similar to Krusell et al. (2010), who solve a random search model with workers who can hold assets.

$z \in Z \subseteq \mathbb{R}_+$ represents her idiosyncratic productivity realisation, and $w \in \mathcal{W} \subseteq [0, 1]$ is her piece-rate wage, if she is employed.

The aggregate state of the economy can be expressed as $\psi = (A, \Omega)$, with $A \in \mathbb{R}_+$ representing the aggregate productivity state of the economy and $\Omega : \{U, E\} \times \mathcal{X} \times \mathcal{Z} \times \mathcal{W} \rightarrow [0, 1]$ denoting the distribution of agents across the states. The aggregate state follows the law of motion $\psi' = Q(\psi)$.

Model timing: At the beginning of each period, the aggregate and individual productivity innovations are revealed. Subsequently, individuals who matched with a vacant firm in the previous period start their new jobs. In the next phase, matches produce and households consume and make their savings choices. In the last stage, firms post vacancies across submarkets and consumers choose the submarket in which to search. Lastly, separations and job-matching take place. In the notation that follows, value functions of the workers are evaluated after production has taken place and wages were paid, but before the consumption/savings decision.

3.2 Firms

An unmatched firm can post a vacancy into a submarket indexed by the worker's productivity z, her cash-on-hand x and the posted wage w'. The value of a vacancy is

$$V_F(z, x, w'; \psi) = -\kappa + \frac{1}{1+r}\mathbb{E}\left[q(\theta)J(z', x', w'; \psi') + (1 - q(\theta))V_F'\right] \tag{5}$$

The vacancy posting cost is κ, $q(\theta)$ represents the probability that the firm will meet a worker and r is the interest rate for investments between period t and $t+1$. If the vacancy is not filled, the firm can post again in the subsequent period. Because the firm's owners are risk neutral, they discount the future at the risk-free interest rate.

A firm that meets a worker in a submarket starts producing output in the subsequent period. It's value is

$$\begin{aligned} J(z, x, w) = Az - w + \frac{1}{1+r'}\mathbb{E}\,[\delta(z')V_{new} & \\ + (1 - \delta(z'))\eta(z, x, w)V_{new} & \\ + (1 - \delta(z'))(1 - \eta(z, x, w))J(z', x', w)] & \end{aligned} \tag{6}$$

The firm produces according to aggregate productivity A and the worker's productivity z. With probability $\delta(z')$, the match dissolves exogenously before the production phase in the next period. If this is not the case, the worker finds a new match on-the-job with probability $\eta(\theta)$). In both cases, the firm has the opportunity to post a vacancy V_{new} again in the following period.

Because entry into all submarkets is free, in equilibrium, the value of posting a vacancy is driven to zero, $V_F = 0$. Utilizing this, it is possible to rewrite Equation (5) as

$$\frac{1}{1+r}\mathbb{E}\left[J(z', x', w'; \psi')\right] = \frac{\kappa}{q(\theta)}$$

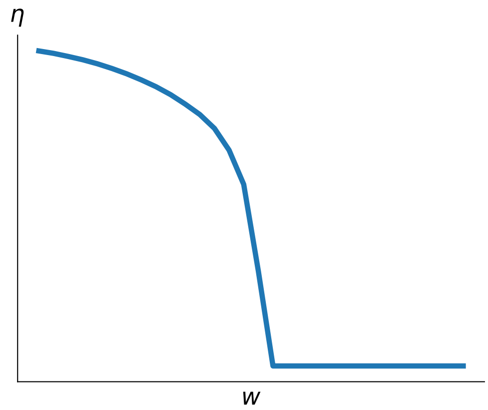
Intuitively, the expected value of a match must be equal to the vacancy posting cost, adjusted for the probability of meeting a worker, in each submarket. This equation pins down the relationship between the wage and tightness for each submarket, conditioning on the workers current productivity z and the worker's savings choice:

$$\theta(z,x,w';\psi) = \begin{cases} q^{-1}\left(\frac{\kappa(1+r)}{\mathbb{E}[J(z',x',w';\psi')]}\right) & \text{if } \mathbb{E}\left[J(z',x',w';\psi')\right] \geq \kappa(1+r) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The inequality constraint implies that firms will not post vacancies in submarkets where the present discounted value of forming a match is too low to cover the vacancy posting cost, even if a match was guaranteed ($q(\theta) = 1$). In these markets, tightness is zero and no matches are formed. To save space, in what follows, I will suppress the dependencies of θ on current productivity z, current worker wealth x and the posted wage w'.

Equation (15) implies, conditioning on productivity and cash-on-hand, a downwards sloping relationship between the workers job-finding probability and the wage across submarkets. Figure 4 illustrates this dependence. On the x-axis are wages offered across submarkets w, on the y-axis is the job-finding probability implied by equation (15). The latter decreases until it hits the wage value at which the expected discounted value of a potential match falls below the vacancy posting cost. At this point, submarket tightness is zero and no firm visits these submarkets.

Figure 4: Relationship between wage and job-finding



Note: This figure illustrates the relationship between the posted submarket wage w and the resulting job-finding probability η, as implied by equation (15). The graph conditions on worker productivity z and cash-on-hand x.

3.3 Worker Problems

3.3.1 Unemployed

The unemployed enter each period with state variables productivity z and cash-on-hand x, and maximize their expected discounted utility. In recursive notation, their problem is

$$\begin{aligned}
V^u(z,x;\psi) = \max_{a'} \quad & u(c) + \beta \max_{w'} \mathbb{E}\Bigg[\underbrace{\eta(\theta)V^e(z',x'_n,w';\psi')}_{\text{Find Work}} \\
& \qquad + \underbrace{(1-\eta(\theta))V^u(z',x'_u;\psi')}_{\text{Stay Unemployed}}\Bigg] \qquad (8) \\
\text{subject to} \quad & x'_u = (1+r)a' + b(z') + h \\
& x'_n = (1+r)a' + (1-\tau)w' \\
& c + a' \leq x
\end{aligned}$$

Using backward induction, households first solve which submarket w' to search in, taking as given the choice for consumption c and savings a'. As discussed in section 3.2, the free entry condition implies that, conditional on worker productivity z and wealth x, a each submarket wage w implies a unique submarket tightness, which pins down a submarket specific job-finding probability $\eta(\theta)$. When choosing the submarket to search in, workers trade off higher piece-rates w', which promise higher continuation values V^w_{t+1} in case a match is formed, with with higher job-finding probabilities. Note that unemployed households who successfully match to a firm cannot immediately separate exogenously. If an unemployed worker matches with a vacant firm, their cash-on-hand in the following period is x'_n. Otherwise, they remain unemployed, receiving benefits $b(z)$, producing h at home, leading to cash-on-hand x'_u.

In the first stage, knowing their choice $w'(a')$, workers choose the optimal consumption in each period, subject to their beginning of period wealth x, their productivity z, and subject to the borrowing constraint.

3.3.2 Employed

Like the unemployed, the employed's problem consists of a consumption-savings choice and a choice over which wage submarket to search in. An employed worker enters the period with individual productivity level z, cash-on-hand x and wage w. Recursively it can be formulated as

$$\begin{aligned}
V^e(z,x,w;\psi) = \max_{a',c} \quad & u(c) + \\
& \beta \max_{w'} \mathbb{E} \Bigg[\underbrace{(1-\delta(z'))(1-\Lambda\eta(\theta)))V^e(z',x'_e,w;\psi')}_{\text{Stay in same job}} \\
& + \underbrace{(1-\delta(z')))\Lambda\eta(\theta)V^e(z',x'_n,w';\psi')}_{\text{Switch jobs}} \\
& + \underbrace{\delta(z')V^u(z',x'_u;\psi')}_{\text{Separations}} \Bigg]
\end{aligned} \tag{9}$$

$$\begin{aligned}
\text{subject to} \quad x'_u &= (1+r)a' + b(z') + h \\
x'_e &= (1+r)a' + (1-\tau)w \\
x'_n &= (1+r)a' + (1-\tau)w' \\
c + a' &\leq x
\end{aligned}$$

Analogous to unemployed's problem, an employed worker's problem can be solved by backward induction. The employed first choose the wage submarket in which they want to search on-the-job, taking savings and consumption decision as given. Each period, the employed are only able to search with probability Λ. Further, with exogenous probability $\delta(z')$, an employed worker becomes unemployed at the beginning of the next period, irrespective of their search outcome.

The employed search in the same submarkets as the unemployed, conditional on their respective savings decisions and productivity. Hence, with probability $\eta(\theta)$, their search is successful and they move to a new wage w' starting in the next period (unless they get separated exogenously). Note, again, that w' and If their job-search is unsuccessful, or they are unable to search, they continue working with their current employer.

Workers who enjoy high levels of idiosyncratic productivity search in submarkets with higher job-finding probabilities and lower wages, relative to their productivities. The reasons are two-fold. First, relative to their productivity level, low-productivity households are more productive at home than their high-productivity counterparts. For the former, this acts as an insurance mechanism, making them demand higher wages (and incur lower job-finding probabilities). However, the level of h is too low to insure the highly productive workers, as their potential wages are multiples higher. Second, because individual level productivity z changes over time, highly productive workers want to insure themselves by matching themselves to an employer. Since wages are fixed for the duration of the match, they stand to gain more from being employed at relatively low wages than from waiting, with the risk of a low productivity realization in the next period.

Due to risk aversion, all households will try to smooth their consumption. Unemployed households with little wealth, whose income is likely to increase, due to a positive job-finding probability, would like to borrow, but are prevented from doing so by the borrowing constraint. To avoid large jumps in their earnings, they search in submarkets that offer low wages and high job-finding probabilities. At the same time, rich unemployed households search in markets with lower job-finding probabilities but higher wages. Through their asset holdings, they are insured against the resulting fluctuations in earnings and the risk associated with them.

This result is similar to those obtained in models with search effort (Baily, 1978; Chetty, 2006), but for slightly different reasons. In those model, search effort is costly, and the wage is constant. Then, richer individuals exert less search effort to find jobs, because the difference in utilities between unemployment and employment is too small to justify paying high search costs. In my model, search is costless and there is no search effort, but agents trade off higher job-finding probabilities with higher wages. All else equal, asset rich individuals search in submarkets that are more risky (lower job-finding probabilities), because they are insured against the earnings fluctuations caused by finding high-paying jobs.

3.4 Government budget

The government collects income taxes and all firm profits, with which it finances a stock of risk free bonds, balancing its budget each period:

$$
\begin{aligned}
B(1+r) + UI &= B' + \tau W + \Pi \qquad (10)\\
\text{where } W &= \int_{i\in\Omega} w_i \quad d\Omega\\
UI &= \int_{i\in\Omega} b_i I_i^U \quad d\Omega\\
A &= \int_{i\in\Omega} a_i \quad d\Omega
\end{aligned}
$$

where B represents the supply stock of bonds at the beginning of period t, $B\prime$ represents newly issued bonds, W is total earnings in the economy and UI is the total outlays of the unemployment insurance system.

The government follows the fiscal rule

$$\tau - \tau^* = \phi_\tau(B' - B^*) \qquad (11)$$

where τ^* and B^* are the steady state tax rate and bond issuance, respectively. The parameter $\phi_\tau > 0$ governs how elastic bond issuance is relative to tax changes. For $\phi_\tau = 0$, taxes are constant and the budget is balanced through bond issuance. As the parameter rises, taxes become more elastic.

3.5 Equilibrium

Recursive Equilibrium definition: A recursive equilibrium in this economy is, given a path for the interest rate r and the labor income tax τ, a set of household savings policy functions $g_a^E(z,x,w;\psi)$ and $g_a^U(z,x;\psi)$, a set of household wage choice functions $g_w^E(z,x,w;\psi)$ and $g_w^U(z,x;\psi)$ and submarket tightnesses $\theta(z,x,w',\psi)$, such that

- the household's asset and wage policy functions are consistent with the problems in Equation (8) and (9),
- the government budget in Equation (10) is balanced,
- the free entry condition implies submarket tightness according to Equation (15),
- asset markets clear, such that

$$B' = \int_{i\in\Omega} g_a^W(z,x,w;\psi) + g_x^U(z,x;\psi) \quad d\Omega$$

- the aggregate state of the economy ψ evolves according to $\psi' = Q(\psi)$

The equilibrium, formulated in this way, is difficult to compute, because the distribution of agents Ω is an infinite-dimensional object. However, the model permits a block recursive formulation, as discussed in Menzio and Shi (2010) and Menzio and Shi (2011), which considerably simplifies the problem by decoupling the decision rules and submarket tightnesses from the distribution. The proposition and the corresponding proof follow Karahan and Rhee (2019), Herkenhoff (2019) and Birinci and See (2019).

Block Recursive Equilibrium (BRE) definition: A block recursive equilibrium is an equilibrium in which, given a path for the interest rate r and the labor income tax τ, the households' policy functions and submarket tightnesses only depend on the aggregate productivity state A, but not on the distribution of agents Ω.

Proposition *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies the Inada conditions; ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, and sets of exogenous productivity processes z and A are bounded; iii) matching function M exhibits constant returns to scale; and iv) All policies are restricted to depend on the aggregate state only through aggregate match productivity, then there exists a unique BRE for this economy*

Proof See Appendix C

4 Calibration

I calibrate the steady state of the model to match a set of labor market moments I observe in my dataset. For this exercise, I set aggregate productivity to $A = 1$, hence there are no aggregate fluctuations. I use the Generalized Method of Moments to minimize the distance between the target moments in the model and the data. Tables 1 to 2 and Figure 5 summarize the model calibration.

The period length in the model is set to one quarter. I set the annual risk-free interest rate to 4%, resulting in a quarterly rate of $r = (1.04)^{\frac{1}{4}} - 1 = 0.0985$. To calibrate the bond supply B, I target the average liquid-asset to income ratio in Germany, which I obtain from the Household Finance and Consumption Survey. I utilize the survey's second wave, which was conducted mainly in 2014. Household asset holdings are categorized into liquid and illiquid following the approach by Kaplan et al. (2014), with slight modifications to the definitions used in their exercise. As household income, I classify the sum of self-reported labor earnings and social transfers, as this come closest to the income measure I observe in the SIAB panel.[13] The resulting average liquid-asset to income ratio for Germany is 4.5.

The utility function for workers is given by

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

where σ represents the coefficient of relative risk aversion. I set this parameter to 2, in line with standard calibrations in the literature.

Labor Market Following Den Haan et al. (2000), labor market matches in the model,

[13] To establish comparability between the HFCS and the SIAB panel, and reliability of the income variable in the HFCS, I calculate median quarterly income in 2014 in both datasets. In the SIAB, individual median income is €5700, while in the HFCS, quarterly household income is €4160. Note that the SIAB values are gross earnings, while the HFCS are net of tax.

from a mass of searchers S and vacancies V, are formed according to the matching function

$$M(S,V) = \frac{SV}{(S^x + V^x)^{\frac{1}{x}}}.$$

This function guarantees that the job-finding and vacancy-filling probabilities lie within the interval $[0,1]$. I set $x = 0.3$. I set the vacancy cost $\kappa = 0.04$ from Hagedorn and Manovskii (2008), diving by 12, as theirs is a weekly model. The exogenous quarterly separation probabilities, $\delta(z)$, are set to match the separation probability in the data, across the distribution. Unemployed households produce h of home production each quarter. In the model, this parameter is closely related to the job-finding probability of the lower quantiles, hence I calibrate it to match the job-finding probability at the low end of the income distribution.

Government In Germany, the replacement rate is 60 % of the last net-wage. In order to save on state variables (past earnings), I model this benefit by indexing unemployment benefits to productivity such that $b(z) = \phi_B z$ with $\phi_B = 0.6$, similar to McKay and Reis (2016). I set the parameter governing the elasticity of the tax rate $\psi_{tau} = 0.1$.

Productivity process The household's productivity z is a combination of aggregate productivity in the economy and the consumer's individual productivity. Both evolve according to AR(1) processes. Individual productivity follows

$$\log(z_{t+1}) = \rho_z \log(z_t) + \epsilon_{t+1} \tag{12}$$

with persistence ρ_z and innovations $\varepsilon \sim N(0, \sigma_\epsilon)$. In the model, I discretize the process to a grid $\{z_1, ..., z_s\}$ with $s = 7$ using the Rouwenhorst method. To calibrate the parameter ρ_z, I estimate the following earnings process for *the continuously employed* in both the model and in the data:

$$\log(y_{i,t+1}) = \rho_y \log(y_{i,t}) + e_{t+1}. \tag{13}$$

in order to exclude labor market transitions, which will be an endogenous outcome of the model. Then, I choose the parameters ρ_z in the productivity process such that the two match. In the data, I residualize earnings in the spirit of Heathcote et al. (2010), by regressing labor earnings on observable characteristics:

$$\log(earn_{i,t}) = \alpha + \gamma_1 X_{i,t} + \gamma_2 T_t + y_{i,t}$$

where $earn_{i,t}$ is an individual's quarterly earnings and $X_{i,t}$ contains an age polynomial, dummies for gender and education. I remove these aspects of the earnings process, because the model does not allow for heterogeneity along these dimensions. Using the variance/covariance structure between earnings observations of periods t and $t+s$, I back-out the parameter $\rho_z = (\mathrm{Cov}(y_t, y_{t+s})/\sigma_\epsilon^2)^{(1/(s-t))}$. As $s \to \infty$ (around $s = 50$), the latter equation converges to $\rho_{y,data} = 0.988$ (around $s = 20$) in the data. To calibrate the volatility of the earnings process, I target the ratio of the average gross earnings between the 25th and the 75th percentile, which is 2.402 in the data. In the model, I set $\rho_z = 0.98$ $\sigma_\epsilon^2 = 0.07$.

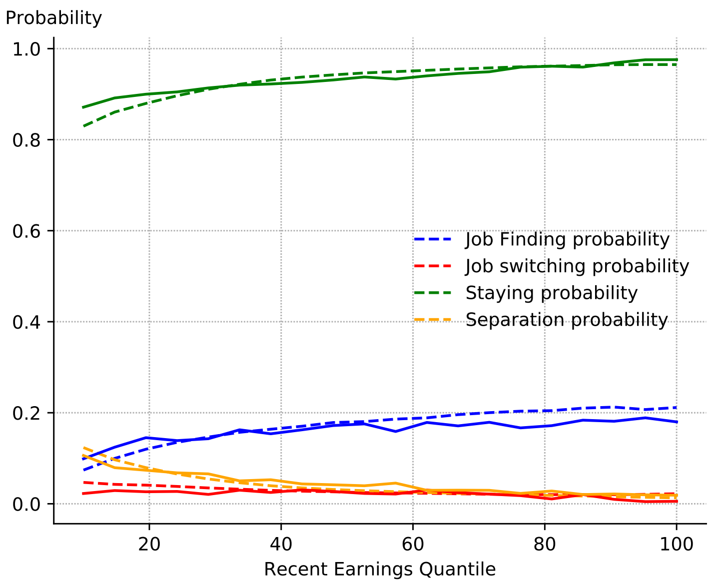
Table 1: Externally Calibrated Parameters

Parameter	Description	Value
r	Interest Rate	0.0985
σ	Coefficient of relative risk aversion	2
ϕ_B	Replacement Rate	0.60
κ	Vacancy posting cost	0.04
ϕ_τ	Persistence of tax rate	0.10

Table 2: Internally Calibrated Parameters

Parameter	Description	Value	Target Moment	Data	Model
B	Bond supply	2.552	Liq. wealth to income	2.670	2.663
λ	OTJ search Probability	0.300	Average switching prob.	0.028	0.022
x	Matching Funct parameter	0.301	Average job finding	0.172	0.175
ρ_z	Persistence of prod. process	0.980	Employed earnings	0.988	0.983
σ_ϵ	Distribution of prod. innovations	0.070	Relative wage $P75/P25$	2.402	2.454
$\delta(z)$	Exogenous separation probability		see text		
h	Home production		see text		

Figure 5: Transition Probabilities - Model and Data



Note: The sample period is 1980-2014.

The calibrated model is able to replicate the transition probabilities in the data fairly well.[14] The separation probabilities in the data were targeted through the exogenous separations probabilities along the productivity grid in the model. Job switching, however was not targeted, and still the model matches the observed switching probabilities in the data fairly well. Furthermore, the job-finding probabilities along the distribution were only targeted using two parameters: home production h and the parameter in the matching

[14] Appendix B shows steady state earnings growth rates in the data and the model.

function x. Still, the model produces job-finding rates which are sloping upwards close to the data. In the next section I describe how the model achieves this.

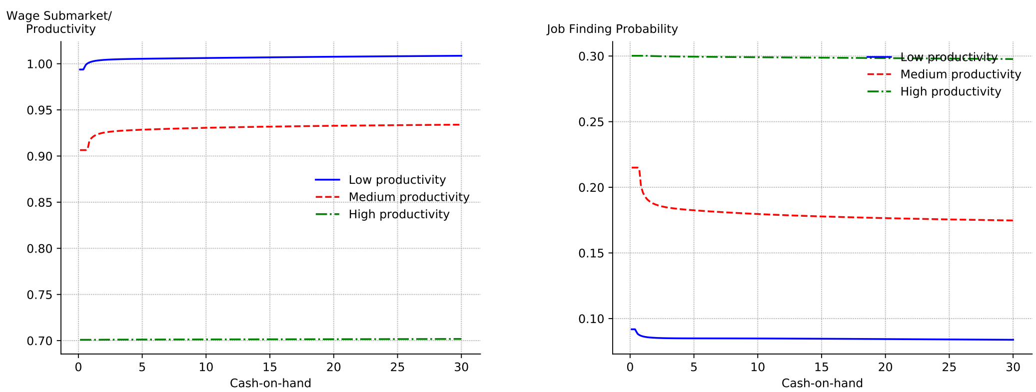
4.1 Policy functions

The job-finding probability along the income distribution is strongly increasing in the model, as in the data. The reason for this is illustrated in the left panel of Figure 6, which shows the search policy functions of the unemployed for different levels of cash-on-hand (x-axis) as well as idiosyncratic productivity (colors) *relative to their productivity realization*. The right panel shows the corresponding job-finding probabilities. Unemployed individuals with higher productivity realizations search in submarkets that offer lower wages, relative to their productivities. The right panel shows that this leads to higher job-finding probabilities for high productivity workers. These workers have a strong incentive to become matched: if they find employment, their wages are fixed, even if their productivity realizations fall in the future.

At the lower end of the productivity spectrum, on the other hand, the unemployed have little incentive to find employment. Their outside option (home-production) is high, relative to their productivity. Furthermore, their productivity may rise in the future, in which case they do not want to be tied to a fixed wage job, anticipating that matched individuals can only search for new jobs with probability $\Lambda < 1$.

Figure 6 also shows search behavior along the wealth (cash-on-hand) dimension. Richer individuals search in submarkets that pay higher wages and offer lower job-finding probabilities, conditional on productivity. This is because individuals with relatively little wealth, while wishing to find work so they can increase their consumption, prefer small fluctuations in their earnings. As they get richer, the unemployed are more able to insure against the large earnings jumps that come from finding a job which pays a high wage. Hence the wage-policy function is upwards-sloping in wealth. Wealth effects, however, are trumped by productivity effects. Only for medium values of productivity do they play a role, and the wage changes associated with them are small.

Figure 6: Submarket choice of the unemployed



(a) Submarket wage relative to productivity

(b) Job-finding probability

Note: This figure shows something

The mechanism for employed workers who search on the job is analogous. Higher productivity realizations make workers search for jobs at relatively low wages that offer high job-finding probabilities, while wealth makes individuals search for jobs that pay higher piece-rates but offer lower job-finding probabilities. Additionally, employed workers take their current wages into account, never searching in wage submarkets that offer lower pay.

5 Results

5.1 Earnings betas in the model

In this section, I show that the model presented in Section 3 can reproduce the heterogeneity in earnings dynamics observed in the data. The earnings betas presented in section 2 are computed as the correlation between individual income growth and aggregate earnings growth. In the model's steady state, aggregate earnings are constant, however. To estimate earnings betas in the model, I introduce aggregate shocks and solve for the economy's response along a series of such shocks over time.

An economy with aggregate shocks requires rational, forward looking agents to take the aggregate state of the economy into account when making their consumption, savings, and wage choices. This state can be summarized by the vector (Ω, A), where Ω is the distribution of agents in the economy and A is the level of aggregate productivity (Krusell and Smith, 1998). Once the model is solved in this general way, the researcher can simulate its response to a series of shocks over time and estimate the earnings betas as the correlation, over time, between aggregate and quantile-specific earnings growth.

The dynamic programming program in an economy with aggregate risk is difficult to solve, as the distribution Ω is an infinite dimensional object. Consequently, the state space, in principle, is infinitely large. I rely on the solution method proposed by Boppart et al. (2018) (BKM), which employs the impulse response to a single unexpected shock in aggregate productivity as a first-order approximation to the full model's response In order for this method to provide accurate results, the model's policy functions, and hence aggregate outcomes, need to be approximately linear in the aggregate productivity shock. Below, I show that this is the case in my model.

I estimate a two impulse responses to aggregate productivity shock of 1% and persistence $\rho = 0.9$. Using this impulse response as a linear approximation of the model to any aggregate productivity shock, I simulate the economy for 600 periods in response to a series of aggregate shocks drawn from a normal distribution with $\sigma_{agg} = 1\%$ and persistence $\rho_{agg} = 0.9$. Along the transition path, I assume that the government balances its budget according to the fiscal rule in Equation (11) by varying both the labor-income tax rate τ_t and bond issuance. Each period, the real interest rate r_t adjusts to clear the asset market. I solve for the path of the tax rate τ_t and the interest rate r_t using the sequence space jacobian method proposed by Auclert et al. (2021).[15]

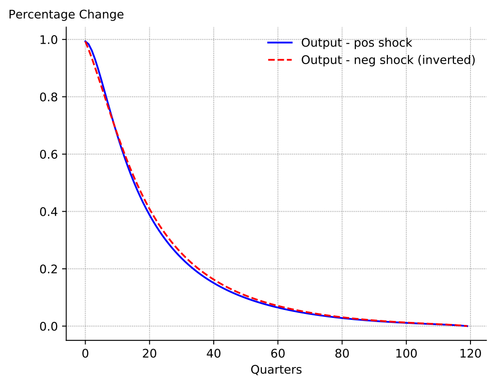
Figure 7, shows the responses of several aggregate variables in response to a 1% increase and decrease in aggregate match productivity. Where feasible, the responses for the negative shock were inverted to facilitate comparison. The impulse responses to the negative productivity shocks are almost perfectly symmetrical to the ones after a positive shock. In response to the positive shock, output increases by close 1 percent upon impact and then converges back to its steady state equilibrium. Wages also increase, but with a lag. This has to do with the structure of the labor market. Upon impact, job

[15]For a discussion of the computation see appendix D.

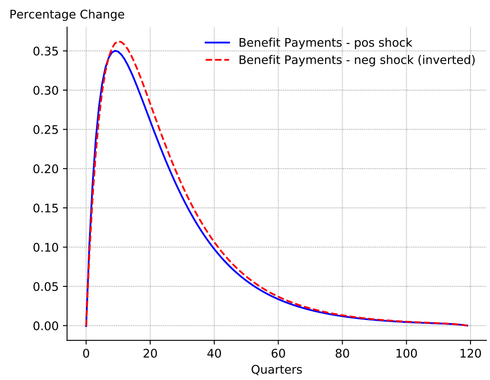
finding increases as firms want to higher workers who will temporarily be more productive. Workers trade off some of the increase in job-finding probability for higher wages. As aggregate productivity converges back to its steady state value, these incentives wane away. The aggregate converges back to steady state as the workers who were hired at higher wages separate from their matches.

The labor income tax falls in response to the shock due to two reasons. Unemployment decreases, which leads to less government expenditures. Additionally, wages rise, implying a larger tax base. In period $t = 0$, as agents in the model are confronted with the new, decreasing path for productivity, they want to save for the worse times ahead and consume less today. To clear the bond market, interest rates fall to dampen the demand for savings.

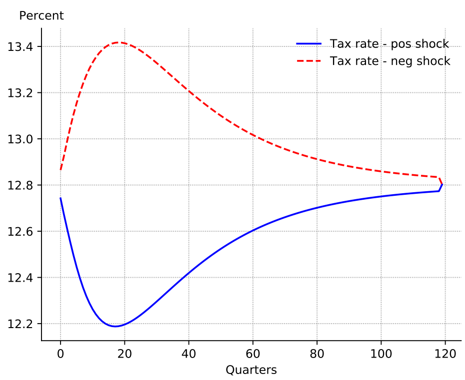
Figure 7: Impulse response to Productivity shock



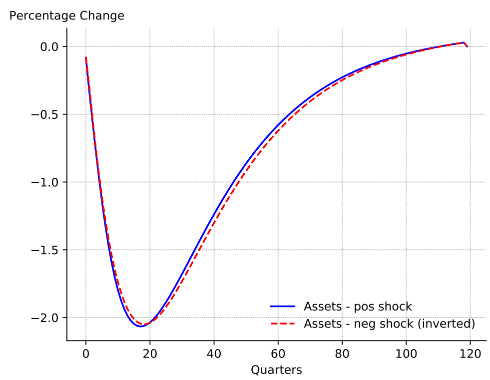
(a) Output



(b) Average wage



(c) Labor income tax



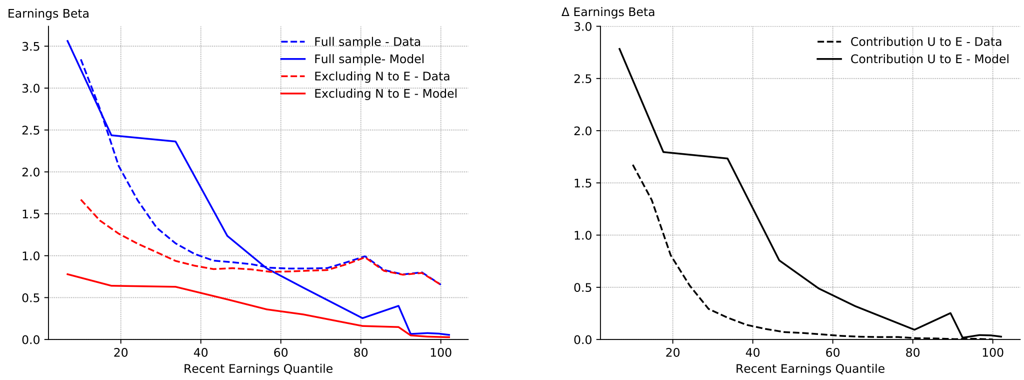
(d) Assets

Note: This Figure shows something

I employ the algorithm proposed by BKM to simulate an economy with aggregate shocks over time. I then construct the model-generated analog to the dataset discussed in section 2 and use it to estimate equation (2), the gross-earnings betas, in the model.

The left panel of Figure 8 shows the result of this exercise. The solid and dashed blue lines represent the model generated beta and the betas estimated in Section 2.3, respectively. The model generated beta coefficients imply that earnings at the bottom of the recent earnings distribution are about three times as procyclical as those around the median, which is in line with the data. At the bottom of the income distribution, the model replicates the steeply decreasing earnings betas, but then briefly flattens out between the second and forth decile. The model also does not replicate the flattening out of the empirical earnings betas beyond the median. Instead, the model implies estimates decrease towards zero. This is intuitive, as in the model, job-stayers earnings are fixed for the duration of a match. As job-staying is the most common transition path for individuals at the top of the earnings distribution, this drives the correlation between aggregate and quantile specific earnings growth to zero.

Figure 8: Model implied earnings betas



(a) Earnings procyclicality decomposition (b) Contribution of job-finding

Note: This Figure shows something

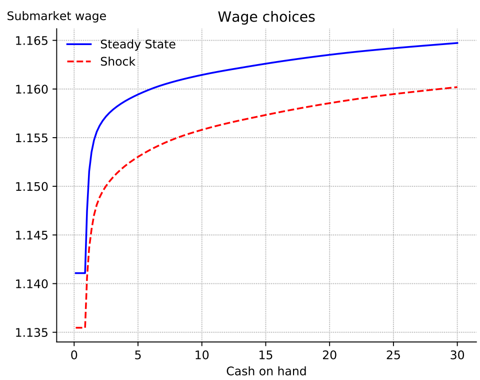
Next, I restrict the sample by excluding individuals who are non-employed in quarter t and employed in quarter $t + 4$. This results in the red dashed (data) and solid (model) lines in the left panel of Figure 8. The difference between the two can be interpreted as the contribution of job-finding to the procyclicality of earnings growth. The difference between the data and the model is more pronounced, with the model implied coefficients falling from 0.5 to zero, while in the data, they fall from close to 1.5 to slightly below one. The level difference, again, is due to the fact that the model does not generate gross-earnings fluctuations for job-stayers, leading the model implied betas to be closer to zero.

An additional comparison between the model and the data can be conducted by comparing the contribution of job-finding to the overall beta coefficients, i.e. the change in the earnings betas when moving from the full sample to a restricted one which excludes job-finding. The result is plotted in the right panel of Figure 8, with the dotted line representing the size of the shaded area in Figure 3b and the solid line representing its model analog. The model, as the data, implies a decreasing contribution of job-finding to the overall beta coefficient. However, it generates a contribution that is considerably larger than that implied by the data. Still, the model qualitatively matches the empirical patters.

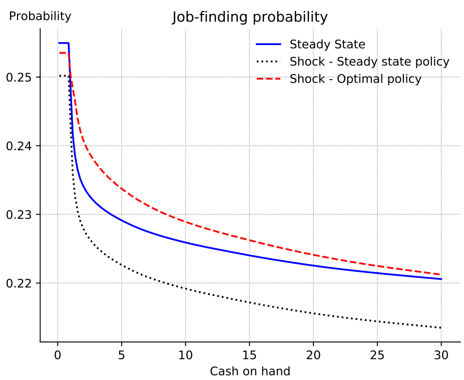
The model is able to generate the patterns observed through the following mechanism. In response to a negative productivity shock, firm value decreases, all else equal. This decrease in match-profits leads fewer firms to enter into all submarkets. Consequently, workers face lower job-finding probabilities if they follow their steady-state wage submarket choices. To counteract some of this decrease, workers can choose to search in lower-wage submarkets, which offer higher job-finding probabilities. The attractiveness of this tradeoff, however, varies across the productivity distribution (and by extension the recent earnings distribution). Furthermore, it is ex-ante unclear how much of the fall in vacancy creation workers can compensate by switching to different submarkets. I investigate this question in section **??**.

Figure 9 summarizes this channel for median productivity individuals (top row) and low productivity individuals (bottom row). The top left panel shows the steady state submarket choices of median productivity individuals in steady state (blue line) and in the first period after the realization of a one-percent decrease in aggregate match productivity. In response to the shock, these agents choose to search in lower-wage submarkets. The top right panel investigates how this affects their job-finding prospects. The blue line shows job-finding probabilities in steady state; after the realization of the shock, job finding probabilities drop for all wealth levels, holding submarket choices fixed (black, dotted line). Due to individuals adjusting their submarket choices, however, job-finding probabilities shift up beyond their steady state values.

Figure 9: Model mechanism

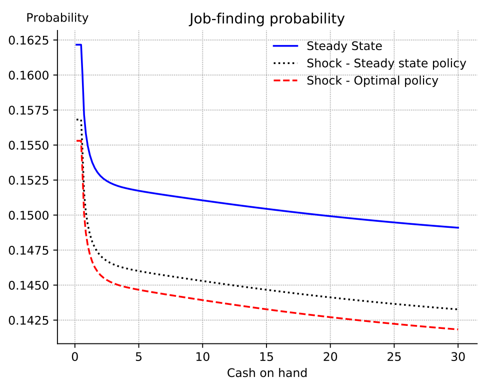


(a) Wage policy, high productivity



(b) Job-finding, high productivity

(c) Wage policy, low productivity



(d) Job-finding, low productivity

Note: This Figure shows something

Analogous to the top left panel, the bottom left panel shows the submarket choices of low productivity individuals. In response to a negative productivity shock, they choose to search in wage-submarkets that offer *higher* wages. This leads their job finding probabilities (bottom right panel) to drop even lower than the hypothetical scenario that keeps policy functions fixed to their steady state values. This is due to the fact that their income from home production (together with unemployment benefits) large, relative to their potential wage earnings. In response to a negative productivity shock, their potential wage earnings fall even further, making non-employment even more attractive. Furthermore, as tax rates increase modestly after a negative productivity shock, low-productivity individuals ask for higher wages to be compensated for this loss, leading to even lower job-finding probabilities.

The mechanism discussed here implies that wages of new matches are procyclical at the top of the income distribution, but countercyclical at the bottom. In the data, the cyclicality of new wages at the low end of the distribution is not countercyclical, but still considerably less cyclical than new wages at the top.

6 Policy Experiments

Using the calibrated model outlined in section 3, I conduct three policy experiments motivated by the observation that earnings risk is higher at the bottom of the income distribution than at the top. First, I introduce a countercyclical hiring subsidy for firms. This policy incentivizes vacancy creation in recessions and allows job-finding to remain closer to its steady state level. Intuitively, this policy weakens the risk to workers caused by a decrease in vacancies, which they cannot counteract by adjusting their search decisions. The second policy experiment considers countercyclical unemployment benefits. This measure offers insurance beyond the steady state unemployment benefit payments in times of negative productivity shocks and decreases insurance when it is not as needed, i.e. in times of positive productivity shocks. The last experiment considers a Universal Basic Income (UBI), which substitutes for and eliminates unemployment benefits. This policy has received much attention in Germany.[16] In 2020, the German Institute for Economic Research started a pilot project on the subject. In the context of the documented heterogeneity in earnings risk, the concept of UBI is interesting as it removes the disincentive on working introduced by unemployment insurance. Hence, it has the potential to encourage workers, to seek out vacancies with higher job-finding probabilities, reducing non-employment at the lower end of the income distribution. In what follows, I introduce all three policies in more detail and compare their welfare effects in the model.

I evaluate the policies according to two measures. First, I calculate the welfare effects of each policy by estimating the percentage increase in consumption necessary in order to make agents indifferent between the two economies, following Krusell et al. (2010):

$$\int_0^1 E_0 \left[\sum_{t=0}^{\infty} \beta^{\mathrm{t}} u\left((1+\lambda) c_{i,t}\right) \right] = \int_0^1 E_0 \left[\sum_{t=0}^{\infty} \beta^{t} u\left(\bar{c}_{i,t}\right) \right] \tag{14}$$

where $c_{i,t}$ is each agent's consumption in the baseline economy and $\bar{c}_{i,t}$ is their consumption in the counterfactual economy. Unfortunately, I cannot calculate this measure in the full aggregate risk version of the model, as I solve it using first-order approximation. For welfare statements, however, a second order approximation would be needed. Instead, I evaluate equation (14) in period 0 after an unexpected, one-time productivity shock. The

[16]For coverage in a major German newspaper, see, e.g.: https://www.zeit.de/wirtschaft/2021-02/bedingungsloses-grundeinkommen-corona-arbeit-existenzangst-finanzierung

value of λ then indicates whether, after such a shock, agents in the model would prefer to live in the baseline or the counterfactual economy.

The second measure, which I can compute along the model's transition path including full aggregate risk, is the volatility of aggregate consumption. A higher cyclicality implies more risk in the model, which is linked to lower welfare.

6.1 Countercyclical hiring subsidies

As outlined above, the goal of the countercyclical hiring subsidy is to dampen the cyclicality of firm vacancy creation. This, in turn, mitigates the countercyclical job-finding risk from the workers perspective.

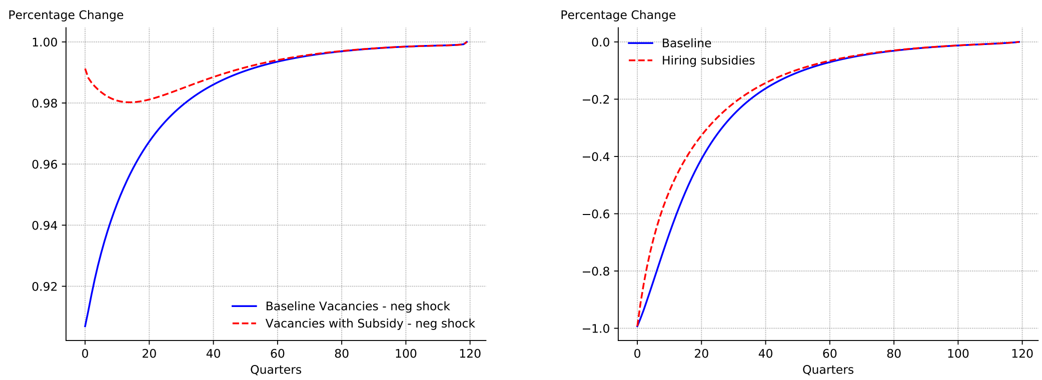
I implement this policy by letting the government award (or tax) firms the lump-sum transfer $v(A)$, indexed by aggregate productivity A, with the following function form:

$$v(A) = \vartheta(A - \overline{A})$$

where the multiplier ϑ is calibrated such that, in response to a negative productivity shock of 1 percent, firms receive a one time transfer which equals the hiring cost: $v(0.99) = \kappa$.

Figure 10 shows the results of this exercise. The left hand panel displays the percentage change in the number of vacancies created in a low-productivity submarket. In the baseline economy, vacancy creation contracts by more than 8 percent. With the subsidy, this fall is reduced considerably: vacancy creation falls by at most 2 percent, and the impulse response is more hump-shaped. Due to the small size of the hiring subsidy, the effect on vacancy creation in high productivity submarkets is small.

Figure 10: Effect of hiring subsidies



(a) Posted Vacancies

(b) Output response to -1% shock

Note: This Figure shows something

The right panel of Figure 10 show the response of aggregate output. As in the baseline economy, output initially contracts by the reduction in aggregate productivity. Afterwards, however, the economy with hiring subsidies rebounds faster.

Welfare, as measured by equation 14, immediately after the realization of a negative, unexpected, transitory shock to aggregate match productivity, increases. To reach the same level of aggregate welfare in the baseline economy, each worker would need to be given an increase of 0.01% in their consumption, forever.

In the model with aggregate risk, the volatility of consumption falls considerably, to 20% of the baseline economy. I conclude, therefore, that hiring subsidies as outlined here benefit the economy by reducing the volatility of consumption over the business cycle.

6.2 Countercyclical unemployment benefits

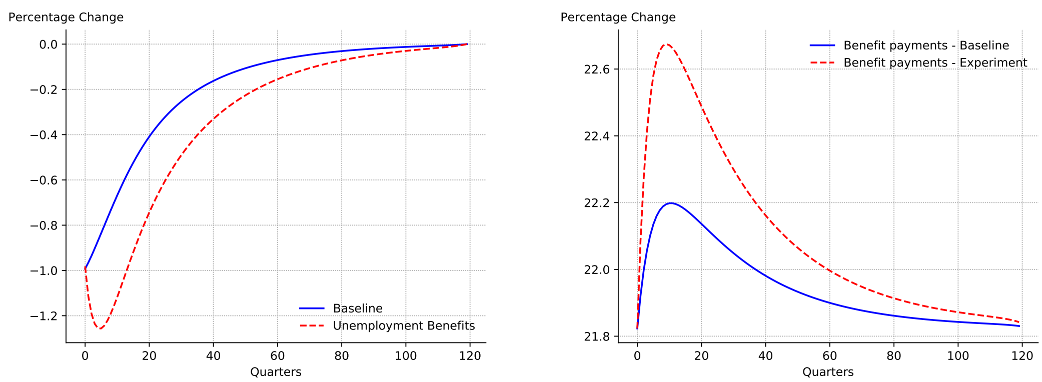
Next, I introduce countercyclical unemployment benefits into the economy. In response to a negative productivity shock, unemployment benefits are supplemented by a lump sum payment of

$$b(A) = \omega(A - \overline{A})$$

where A is the current level of aggregate match productivity and $\overline{A}$ is its steady state value. I calibrate the size of the benefits to have similar fiscal impact as the hiring subsidies, which implies $\omega = 1.5$.

Figure 12 shows the effect of introducing this policy into the baseline economy. The left panel shows that the output response to a negative productivity shock becomes hump-shaped. While in the baseline, output immediately converges back to its steady state level, output in the counterfactual economy drops by 1.2 percent before converging back to steady state. The reason for this is shown in the right panel of the same figure. Non-employment rises by much more when unemployment benefits are countercyclical.

Figure 11: Effect of countercyclical unemployment benefits



(a) Output response to -1% shock (b) Nonemployment response to -1% shock

Note: This Figure shows something

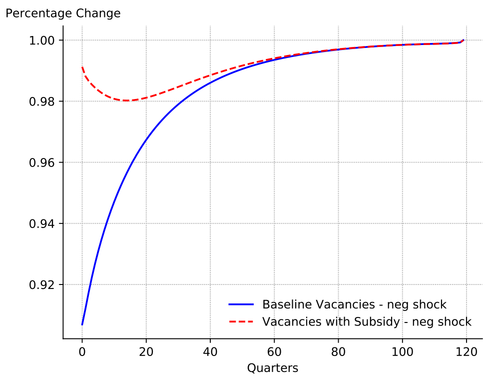
The reason for these findings are related to the incentive effects of unemployment benefits in the model. Higher benefits lead individuals to search in submarkets which offer lower job-finding probabilities, decreasing job-finding. In the context of this model, this is the moral hazard effect of unemployment insurance provision.

The welfare effect of providing unemployment benefits, according to equation 14 is positive. After the realization of a negative productivity shock, individuals in the baseline economy are willing to give up 0.004% of their consumption every quarter in order to live in an economy with the unemployment benefit supplement described here. Hence, relative to the positive insurance effect of higher benefits, However, the variance of logarithmic aggregate consumption increases almost four-fold, relative to the baseline economy.

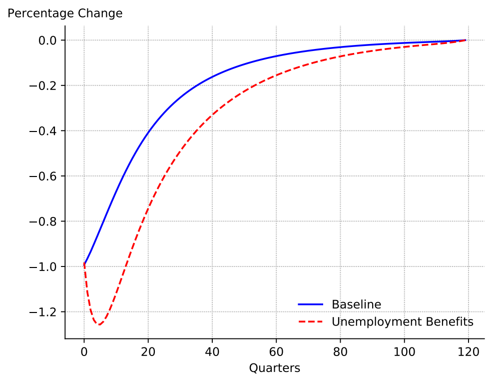
To investigate the moral hazard effect further, I introduce a lump sum increase of unemployment benefits into the baseline economy, but do not allow workers to reoptimize their submarket choices. This turns off the moral hazard effect of unemployment benefit provision. In spirit this exercise is similar to Baily (1978) and Chetty (2006), calculating a statistic akin to the partial derivative of benefit provision, while holding search constant. In the model, $\lambda_{nochoice} = 1.3\%$, implying a welfare increase. However, allowing workers to adjust their choices leads to $\lambda_{GE} = -1\%$.[17] I conclude that in the model presented here, the moral hazard effect of unemployment provision strongly dominates the insurance effect it provides.

6.3 Universal Basic Income

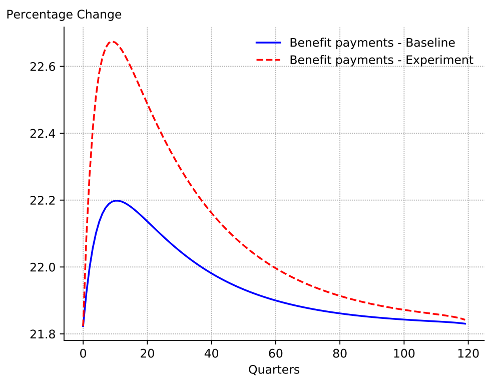
Figure 12: Effect of Universal Basic Income



(a) Earnings procyclicality



(b) Output response to -1% shock



(c) Nonemployment response to -1% shock

Note: This Figure shows something

[17] The effect sizes are larger than those from the cyclical benefit experiment, because here, I increase benefits forever, not just in response to a productivity shock.

7 Conclusion

References

Auclert, A., B. Bardóczy, M. Rognlie, and L. Straub (2021). Using the sequence-space jacobian to solve and estimate heterogeneous-agent models. *Econometrica 89*(5), 2375–2408.

Baily, M. N. (1978). Some aspects of optimal unemployment insurance. *Journal of public Economics 10*(3), 379–402.

Birinci, S. and K. See (2019). How should unemployment insurance vary over the business cycle? *FRB St. Louis Working Paper* (2019-022).

Boppart, T., P. Krusell, and K. Mitman (2018). Exploiting mit shocks in heterogeneous-agent economies: the impulse response as a numerical derivative. *Journal of Economic Dynamics and Control 89*, 68–92.

Broer, T., J. Kramer, and K. Mitman (2020). The curious incidence of shocks along the income distribution. Technical report, Discussion paper, IIES, Stockholm.

Busch, C., D. Domeij, F. Guvenen, and R. Madera (2018). Asymmetric business-cycle risk and social insurance. Technical report, National Bureau of Economic Research.

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly journal of economics 128*(3), 967–1015.

Chaumont, G. and S. Shi (2018). Wealth accumulation, on-the-job search and inequality. *On-the-Job Search and Inequality (July 24, 2018).*

Chetty, R. (2006). A general formula for the optimal level of social insurance. *Journal of Public Economics 90*(10-11), 1879–1901.

Dany-Knedlik, G., A. Kriwoluzky, and S. Pasch (2021). Income business cycles.

De Nardi, M., G. Fella, M. Knoef, G. Paz-Pardo, and R. Van Ooijen (2021). Family and government insurance: Wage, earnings, and income risks in the netherlands and the us. *Journal of Public Economics 193*, 104327.

Den Haan, W. J., G. Ramey, and J. Watson (2000). Job destruction and propagation of shocks. *American economic review 90*(3), 482–498.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009). Revisiting the german wage structure. *The Quarterly journal of economics 124*(2), 843–881.

Eeckhout, J., A. Sepahsalari, et al. (2020). The effect of wealth on worker productivity. Technical report, School of Economics, University of Bristol, UK.

Ganzer, A., A. Schmucker, P. Vom Berge, and A. Wurdack (2017). Sample of integrated labour market biographies-regional file 1975-2014. *FDZ-Datenreport 1*, 2017.

Guvenen, F., F. Karahan, S. Ozkan, and J. Song (2015). What do data on millions of us workers reveal about life-cycle earnings risk? Technical report, National Bureau of Economic Research.

Guvenen, F., S. Ozkan, and J. Song (2014). The nature of countercyclical income risk. *Journal of Political Economy 122*(3), 621–660.

Guvenen, F., S. Schulhofer-Wohl, J. Song, and M. Yogo (2017). Worker betas: Five facts about systematic earnings risk. *American Economic Review 107*(5), 398–403.

Hagedorn, M. and I. Manovskii (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review 98*(4), 1692–1706.

Halvorsen, E., H. Holter, K. Storesletten, S. Ozkan, et al. (2019). Dissecting idiosyncratic income risk. In *2019 Meeting Papers*, Number 1337. Society for Economic Dynamics.

Harmenberg, K. and H. H. Sievertsen (2017). The labor-market origins of cyclical income risk.

Heathcote, J., F. Perri, and G. L. Violante (2010). Unequal we stand: An empirical analysis of economic inequality in the united states, 1967–2006. *Review of Economic dynamics 13*(1), 15–51.

Herkenhoff, K. F. (2019). The impact of consumer credit access on unemployment. *The Review of Economic Studies 86*(6), 2605–2642.

Hoffmann, E. B. and D. Malacrino (2019). Employment time and the cyclicality of earnings growth. *Journal of Public Economics 169*, 160–171.

Holm, M. B., P. Paul, and A. Tischbirek (2020). The transmission of monetary policy under the microscope. Federal Reserve Bank of San Francisco.

Hubmer, J. (2018). The job ladder and its implications for earnings risk. *Review of Economic Dynamics 29*, 172–194.

Kaplan, G., G. L. Violante, and J. Weidner (2014). The wealthy hand-to-mouth. Technical report, National Bureau of Economic Research.

Karahan, F., S. Ozkan, and J. Song (2019). Anatomy of lifetime earnings inequality: Heterogeneity in job ladder risk vs. human capital. *FRB of New York Staff Report* (908).

Karahan, F. and S. Rhee (2019). Geographic reallocation and unemployment during the great recession: The role of the housing bust. *Journal of Economic Dynamics and Control 100*, 47–69.

Kitao, S., A. Şahin, and J. Song (2011). Hiring subsidies, job creation and job destruction. *Economics Letters 113*(3), 248–251.

Krueger, D., K. Mitman, and F. Perri (2016). Macroeconomics and household heterogeneity. In *Handbook of Macroeconomics*, Volume 2, pp. 843–921. Elsevier.

Krusell, P., T. Mukoyama, and A. Şahin (2010). Labour-market matching with precautionary savings and aggregate fluctuations. *The Review of Economic Studies 77*(4), 1477–1507.

Krusell, P. and A. A. Smith, Jr (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy 106*(5), 867–896.

McKay, A. and R. Reis (2016). The role of automatic stabilizers in the us business cycle. *Econometrica 84*(1), 141–194.

Menzio, G. and S. Shi (2010). Block recursive equilibria for stochastic models of search on the job. *Journal of Economic Theory 145*(4), 1453–1494.

Menzio, G. and S. Shi (2011). Efficient search on the job and the business cycle. *Journal of Political Economy 119*(3), 468–510.

Mitman, K. and S. Rabinovich (2015). Optimal unemployment insurance in an equilibrium business-cycle model. *Journal of Monetary Economics 71*, 99–118.

Mueller, A. I. (2017). Separations, sorting, and cyclical unemployment. *American Economic Review 107*(7), 2081–2107.

Pruitt, S. and N. Turner (2020). Earnings risk in the household: Evidence from millions of us tax returns. *American Economic Review: Insights 2*(2), 237–54.

Storesletten, K., C. I. Telmer, and A. Yaron (2004). Cyclical dynamics in idiosyncratic labor market risk. *Journal of political Economy 112*(3), 695–717.

A Robustness

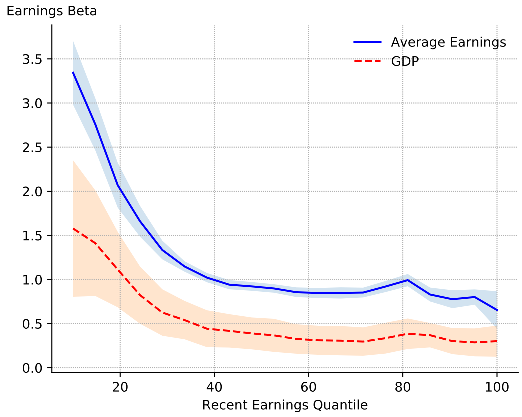
A.1 GDP

For robustness, I construct a second aggregate earnings growth measure using GDP. Growth is measured as the quarter-on-quarter log difference in real GDP between periods t and $t+k$ [18]:

$$\Delta Y_{t,k}^{GDP} = \log(GDP_{t+k}) - \log(GDP_t)$$

Figure 13: Earnings beta with GDP

I then substitute $\Delta Y_{t,k}^{GDP}$ into equation (2) and estimate the beta coefficients. Figure 13 reports the results from this exercise. While the beta-coefficients are shifted downwards, implying a lower cyclicality of quantile-specific earnings relative to GDP, the shape of the curve remains similar. Earnings at the bottom of the income distribution are still about three-times as procyclical as those at the top.



Note: This figure shows something

A.2 Asymmetry

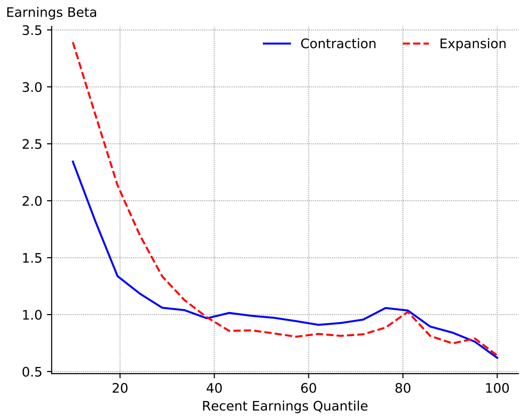
The heterogeneity in the cyclicality of earnings growth outlined in section 2.3 raises the question whether the effect is symmetric between expansions and contractions of the business cycle. To investigate this issue, I obtain an OECD based recession indicator[19], which identifies the time-period between the peak and trough values of recessions. Using this indicator, I reestimate Equation (2), separating the sample into expansions and contractions. Figure 14 presents the results for β_Y^q along the recent earnings distribution, employed average earnings as the measure of aggregate earnings.

[18] Deflated, seasonally and calendar adjusted GDP is obtained from the German Statistical Office. Due to German reunification in 1990, there only exist two separate time series for (i) West Germany and (ii) today's Germany, but both contain values for 1991. Consequently, I normalize both series by the GDP values for the first quarter of 1991 and append them.

[19] The indicator is constructed by the Federal Reserve Bank of Saint Louis, the variable name is DEUREC.

Similar to the results in Figure 3, earnings are more procyclical at the bottom of the earnings distribution. The procyclicality is fairly symmetrical, between expansions and contractions, with betas estimated the former slightly larger than those of the latter. One possible reason for this difference are employment protection schemes like short-time work, by which employers are subsidised in order to keep employees on their payroll. The asymmetry decreases as one moves up along the distribution, almost vanishing beyond the seventh quantile. These results indicate that the cyclicality in earnings observed especially at the bottom of the distribution is not driven solely by either expansions or contractions. Conversely, earnings at the bottom are highly correlated with the aggregate during both periods.

Figure 14: Cyclicality of earnings – Asymmetry

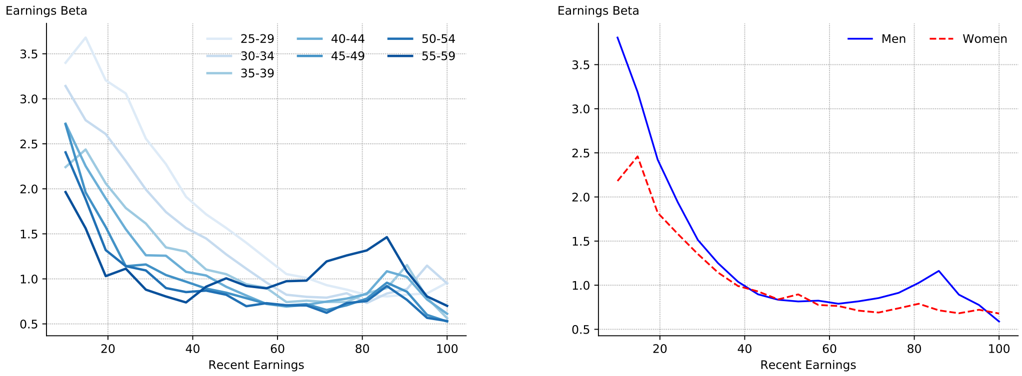


Note: This figure shows the coefficient $\beta^q_{Y,k}$ from Equation (2) by quantile, estimated during periods of contraction (blue) and expansion (red), respectively. Contractionary periods are identified based on the OECD's recession indicator. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

A.3 Age and Gender

In the graphs presented so far, all quantiles are constructed within age-gender bins. However, it is of course of interest how the earnings betas differ along those dimensions, as well. Figure 15, therefore, shows the estimates of β^q_Y for quantiles based on recent earnings separately for each age group (left panel) and each gender (right panel).

Figure 15: Cyclicality of earnings – Age and Gender



(a) Earnings Beta – Age

(b) Earnings beta – Gender

Note: The *Left Panel* shows the coefficient $\beta^q_{Y,k}$ from Equation (2) by quantile, estimated for subsamples of different five-year age groups. The *Right Panel* plots the coefficient $\beta^q_{Y,k}$ from Equation (2) by quantile, for men (blue) and women (red). Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

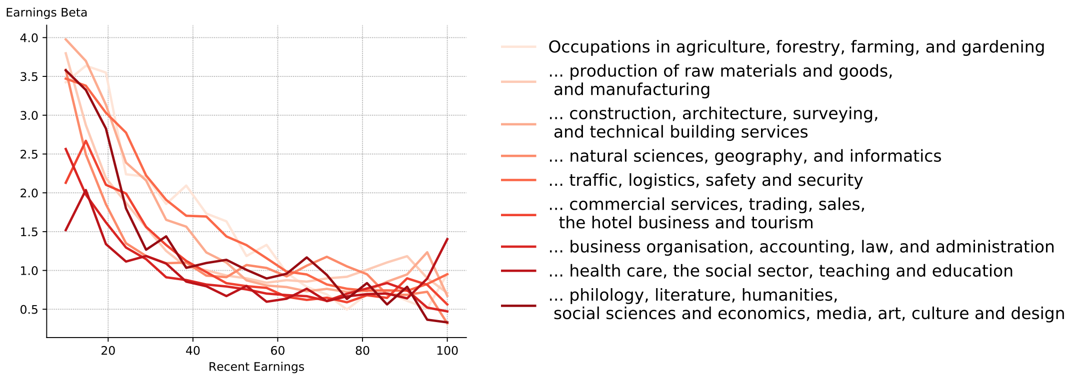
Similar to results presented in Guvenen et al. (2017), the size of the β^q_Y, as well as their heterogeneity, diminish with age (with the exception of the top earners of the last age group, where growth rates are imputed). While earnings growth of individuals between the ages of 25 and 34, at the bottom of the earnings distribution, moves with aggregate earnings by a factor of 3, this coefficient diminishes to 2 along the life-cycle. Towards to top of the distribution, procyclicality is weaker at all ages.

Earnings growth at the bottom is considerably more procyclical for men than it is for women as their β^q_Y is almost 50% larger. However, towards the median of the recent earnings distribution, the two graphs converge. At the very top, the two groups diverge again, potentially due to the fact that considerably more male earnings observations are censored and hence imputed. Hence, the stark difference is to be taken with a grain of salt.

A.4 Occupation and Industry

Another potential driver of the heterogeneous cyclicality in earnings growth rates are an individuals occupation or industry. Hence, again, I reestimate Equation (2), splitting the sample into ten separate occupation bins. Figure 16 presents the results. The familiar picture of a higher correlation between individual and aggregate earnings growth at the bottom of the distribution is present in all occupations, but to varying degrees. Among the most cyclical occupations related to construction and manufacturing, moving 3:1 with average earnings in the first quantile. In the same quantile, occupations related to health care and science only co-move slightly 2:1 with the aggregate. Towards the median quantile, all graphs converge towards a value between 0.5 and 1.

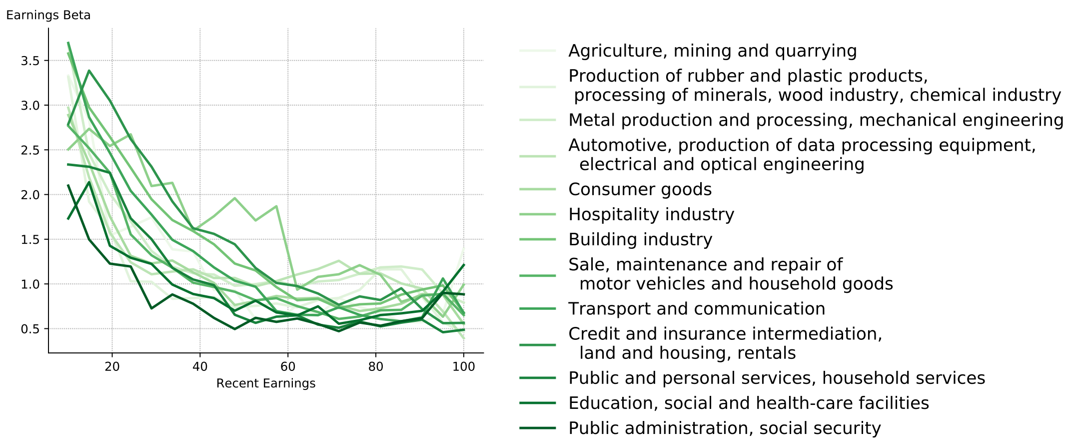
Figure 16: Cyclicality of earnings – Occupation



Note: The figure shows the coefficient $\beta^q_{Y,k}$ from Equation (2) by quantile, estimated for subsamples of different occupational groups. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

Figure 17 shows the results of performing a similar analysis separately by industry. For all industries, there is a strong downward trend in procyclicality as one moves up across quantiles. The least cyclical industry, for most quantiles, is public administration. Among the most cyclical are the automotive industry and agriculture.

Figure 17: Cyclicality of earnings – Industry



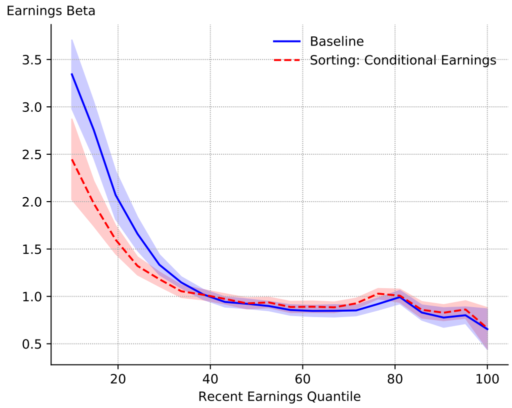
Note: The figure shows the coefficient $\beta^q_{Y,k}$ from Equation (2) by quantile, estimated for subsamples of different industry groups. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The sample period is 1980-2014.

A.5 Quantile ordering with Conditional earnings

In the baseline estimation of the earnings betas, I sort individuals into quantiles based on their earnings history over the previous five years, including zero-earnings spells, i.e., unconditional earnings. Alternatively, individuals can be sorted according to their conditional earnings history, i.e., excluding zeros. This measure is likely closer to individual level productivity, holding constant age and gender.

Figure 18 shows the result of this alternative sorting method on the earnings beta estimations (blue) and the baseline estimation discussed above (red). Sorting individuals based on conditional earnings considerably lowers the earnings beta for the bottom quantiles, but does not alter the general shape of the graph, which still indicates that those at the lower end of the (now conditional) earnings distribution receive earnings which are much more correlated with the aggregate business cycle than those further up in the same distribution.

Figure 18: Alternative Sorting – Conditional Earnings



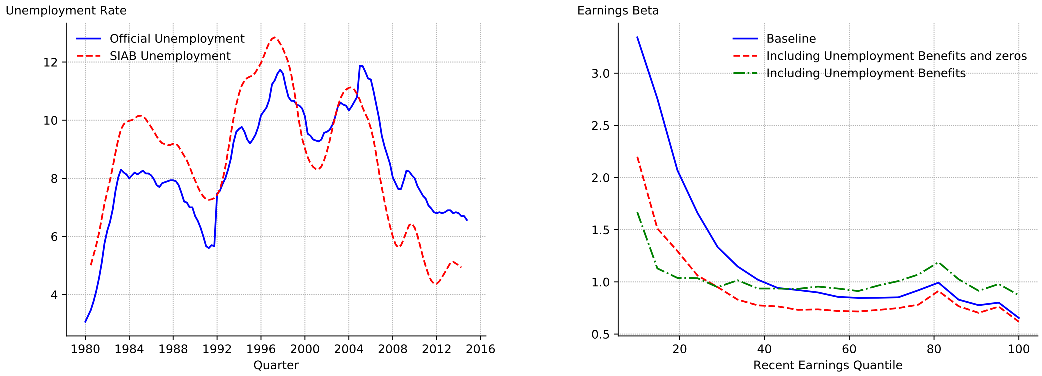
Note: This figure shows the coefficients $\beta^{q}_{Y,k}$, from equation (2), by quantile. Individuals are sorted into 20 quantiles each quarter based on their most recent five-year earnings history. The blue line plots the coefficient when zero-earnings observations are included in this earnings history, the red line conditions on employment and excludes zeros from the earnings history. The sample period is 1980-2014.

A.6 Unemployment benefits

As outlined in footnote 4 the only consistent measure of unemployment benefits in the data are Unemployment Benefits I. They are paid out for a limited period of time after job-loss with a replacement rate of 65%. The left panel of Figure 19 compares the official German Unemployment rate[20] (red) to the one obtained using the SIAB sample (blue). To make the series comparable, I seasonally adjust the SIAB unemployment rate. From 1980 to 1998, the SIAB sample overestimates the unemployment rate by close to two percentage points. After 2000, the pattern reverses and it underestimates unemployment, especially towards the end of the sample. However, the dynamics of the two unemployment rates are very similar over time. Note that the duration of unemployment benefit receipts was shortened to 12 months in 2005, potentially leading to fewer observed unemployed individuals after that period.

[20] I obtain the Quarterly Registered Seasonally Adjusted Unemployment Rate for Germany from Fred (LMUNRRTTDEQ156S) .

Figure 19: Cyclicality of earnings – Unemployment benefits



(a) Put unemployment rate here (b) Earnings betas – Unemployment benefits

Note: The *Left Panel* shows the official German unemployment rate (blue) and the unemployment rate implied by the SIAB sample (red). The official unemployment rate is constructed for West-Germany during the years before 1990. The *Right Panel* shows the coefficients $\beta^q_{Y,k}$, from equation (2), by quantile. The blue line represents the baseline model, which sets earnings to zero during non-employment spells. The red line shows the coefficients when unemployment benefits are included as earnings for the non-employed. The green line restricts the sample of the non-employed only to those individuals who receive unemployment benefits.

Here, I investigate the consequences of including non-employed earnings in the baseline estimation by reestimating Equation (2) while including the observed benefits as earnings for the unemployed. I perform two robustness tests: (i) keeping earnings at zero for all non-employed individuals who are not unemployed (ii) excluding all non-employed individuals who are not unemployed. The former approach uses the same sample as the baseline, only changing earnings for some non-employed, while the second approach produces a smaller sample. Both approaches require new quantiles to be calculated.

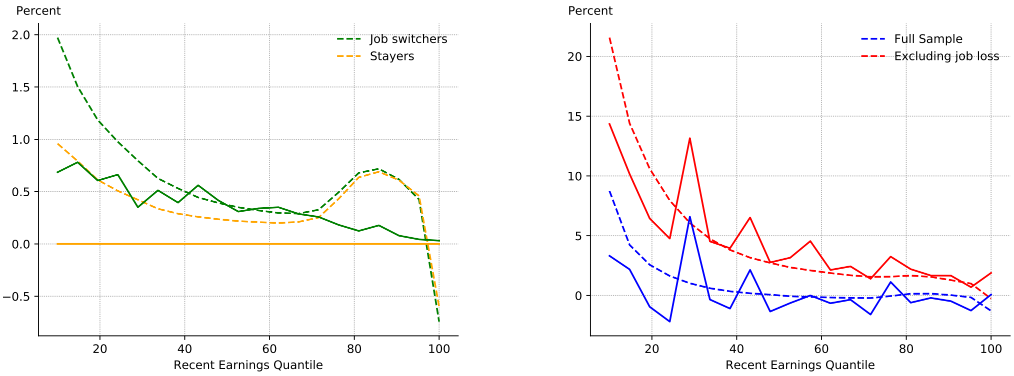
The left panel of Figure 19 compares the baseline estimation, previously reported in Figure 3 (blue) to the two alternative approaches, including zero earnings for the non-unemployed non-employed (yellow) and excluding the non-unemployed non-employed (red). The Figure shows that the earnings betas at the bottom get progressively smaller with each step. When moving from the baseline to including non-employment earnings, this is intuitive, as unemployment benefits introduce an insurance mechanism that smooths the strongest earnings fluctuations. Not also that there is almost no difference between the two lines at the very top, implying that unemployment transitions are less important here.

Excluding zeros for the non-unemployed non-employed leads the betas at the bottom to fall further. This is likely due to a reshuffling of individuals across percentiles, dampening the effects seen in the other two graphs. Beyond the 6th quantile, the quantile specific earnings betas are slightly higher than using the other two approaches.

B Additional calibration results

As described in the section 4, the calibration explicitly targets labor market transition probabilities. However, it leaves earnings growth rates across the distribution untargeted. Figure 20 shows the earnings growth rates that result from the model. The left panel compares the results along the intensive margin. In the model, job-stayers earnings are flat, by definition, as wages are fixed for the duration of a match. Job switchers' earnings growth, however, decreases in both the model and the data. The model underestimates the slope, especially at the bottom of the distribution. Furthermore, it cannot produce the increase in switchers' earnings growth at the very top of the distribution.

Figure 20: Steady State earnings growth rates



(a) Earnings growth along the intensive margin

(b) Earnings growth along the extensive margin

Note: The *Left Panel* shows a comparison between quarterly growth-rates implied by the model and the same statistic measured in the data. Dashed lines represent the data, dashed lines represent the model's output. The yellow lines plot earnings growth for job-stayers, the yellow line for job-switchers. The *Right Panel* shows earnings growth rates along the extensive margin. The blue line represents earnings growth for the full all workers, the red line excludes job-loss. The dashed lines represent the data, the solid lines represent the model's output.

The right panel compares earnings growth along the extensive margin in the model and the data. Both produce downwards sloping earnings growth rates. The model's output exhibits pronounced humps, however. This is due to the fact that agents are not smoothly distributed over different levels of recent earnings. A specific level of recent earnings, say R, is reached by agents who make very different decisions from those who reach level $R+1$. This can lead to the non-smoothness of earnings growth rates along the distribution.

C Block recursive equilibrium

Block recursive equilibrium (BRE) definition: A block recursive equilibrium is an equilibrium in which, given a path for the interest rate r and the labor income tax τ, the households' policy functions and submarket tightnesses only depend on the aggregate productivity state A, but not on the distribution of agents Ω.

Proposition *If i) utility function $u(\cdot)$ is strictly increasing, strictly concave, and satisfies the Inada conditions; ii) choice sets $\mathcal{W}$ and $\mathcal{A}$, and sets of exogenous productivity processes z and A are bounded; iii) matching function M exhibits constant returns to scale; and iv) All policies are restricted to depend on the aggregate state only through aggregate match productivity, then there exists a unique BRE for this economy*

Proof As mentioned in the body of the paper, the proposition and the proof closely follow Karahan and Rhee (2019), Herkenhoff (2019) and Birinci and See (2019).

I prove the existence of a block recursive equilibrium in two steps. The first step is showing that the firms' value functions and the resulting market tightnesses only depend on the aggregate state ψ through aggregate productivity A, **given a tax rate** τ **and an interest rate** r. The second step shows that the households' policy and value functions are similarly independent of the distribution of agents γ, **given** τ **and** r. Consequently, there is a solution to the households' problem which, together with the solution to the firms' problems and the resulting market tightnesses constitutes a BRE, as long as τ and r are given. Note that I condition on the tax rate τ and the interest rate r, two objects which, in order to clear the government budget and the asset market, will depend on the aggregate distribution of workers across states.

Let $\mathcal{J}(\mathcal{Z}, \mathcal{X}, \mathcal{W}, \mathcal{A}|\tau, r)$ be the set of continuous and bounded functions which map $\mathcal{J} : \mathcal{W} \times \mathcal{X} \times \mathcal{W} \times \mathcal{A} \to \mathbb{R}$, given a tax rate τ and an interest rate r. Further, let $\mathbf{T}_{\mathcal{J}}$ be the operator associated with the firm's value function, Equation (6). One can verify, using Blackwell's sufficiency conditions, that $\mathbf{T}_{\mathcal{J}} : \mathcal{J} \to \mathcal{J}$ is a contraction, the unique fixed point of which I denote as $J^* \in \mathcal{J}$. From this, it follows that the firm's value function only depends on the aggregate state ψ through the state of aggregate productivity A. In turn, this implies that the wage posting choices by firms, conditional on worker wealth $\mathcal{X}$ and worker productivity $\mathcal{Z}$, are also only affected by the aggregate state ψ through aggregate productivity A. Upon substituting J^* into Equation 15, I obtain

$$\theta^*(z, x, w'; A) = \begin{cases} q^{-1}\left(\frac{\kappa(1+r)}{\mathbb{E}[J^*(z', x', w'; A')]}\right) & \text{if } w \in \mathcal{W}(z, x, w; A) \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

This condition shows that market tightness does not depend on the distribution of agents across states, Γ, apart from the interest rate r, which I am conditioning on.

Next, I move the the workers' problems. I combine all value functions into a single functional equation and show that this equation is a contraction. It can be shown that this function maps the set of functions which depend on the aggregate state ψ only through aggregate productivity A. This function V is of the form $V : \{U, E\} \times \mathcal{X} \times \mathcal{Z} \times \mathcal{W} \times \Omega \to \mathbb{V}$, where Ω defines all possible realizations of the aggregate state. In this formulation,

$$V(U, z, x; \psi) = V^U(z, x; \psi|\tau, r)$$
$$V(E, z, x, w; \psi) = V^E(z, x, w; \psi|\tau, r)$$

I now define a set of functions $\mathcal{V} : \{U, E\} \times \mathcal{X} \times \mathcal{Z} \times \mathcal{W} \times \mathcal{A} \to \mathbb{V}$ and let $\mathbf{T}_V$ be an operator such that

$$
\begin{aligned}
(T_V V) = & \mathbb{I}_U \left\{ \max_{c_U} \quad u(c_U) + \beta \left[\max_{w'} \mathbb{E} \left[\eta(\theta(z,x,w';A|\tau,r)) V(E,z',x'_n,w';A'|\tau,r) \right.\right.\right. \\
& \quad + \left.\left.\left. (1-\eta(\theta(z,x,w';A|\tau,r)))V(U,z',x'_u;A'|\tau,r) \right]\right]\right\} \\
& \quad \mathbb{I}_E \left\{ \max_{a',c} \quad u(c) + \beta \max_{w'} \mathbb{E} \left[\right.\right. \\
& \quad (1-\delta(z'))(1-\Lambda\eta(\theta(z,x,w';A|\tau,r)))V(E,z',x'_e,w;A'|\tau,r) \\
& \quad + (1-\delta(z'))\Lambda\eta(\theta(z,x,w';A|\tau,r))V(E,z',x'_n,w';A'|\tau,r) \left.\right] \\
& \quad + \left.\delta(z')V(U,z',x'_u;A'|\tau,r) \right\}
\end{aligned}
$$

subject to

$$
\begin{aligned}
c + a' &\leq x \\
x'_u &= (1+r)a' + b(z') + h \\
x'_e &= (1+r)a' + (1-\tau)w \\
x'_n &= (1+r)a' + (1-\tau)w' \\
A' &= F_A(A) \\
z' &= F_Z(z).
\end{aligned}
$$

In this formula, I use the fact that submarket tightness θ does not depend on the aggregate distribution of workers across states. Further, x_u is the cash-on-hand of unemployed workers, x_n is the cash-on-hand value for workers who find a new job at w' and x_e is the cash-on-hand value for workers who stay employed at wage w. The first two lines represent the problem of an unemployed worker, the last three lines represent the problem of an employed worker.

If we assume that the utility function is bounded and continuous, then $\mathcal{V}$ is a set of bounded and continuous functions. It can be shown that the operator T_V maps $\mathcal{V} \to \mathcal{V}$. Using Blackwell's sufficiency conditions for a contraction and the assumptions on the boundedness of the sets defining the exogenous processes $\mathcal{Z}$ and $\mathcal{A}$, as well as the choice sets $\mathcal{W}$ and $\mathcal{X}$, one can show that T_R is a contraction with a fixed point $V^* \in \mathcal{V}$. Thus, the solution to the workers' problem does not depend on the distribution of workers across states Ω. This, in combination with the firm's problem above, constitutes a block recursive equilibrium.

D Computational appendix

To solve the model in steady state, I employ the following algorithm:

- Guess values for τ and r
- Solve the firms' and the workers' problems
  - Guess wage and consumption policy functions for the workers
  - Given these policies together with the free entry condition, solve the firms' problem
  - Given the resulting job-finding probabilities and taking wage choices as given, update the consumption policy function using an endogenous grid point method

  - Given the job-finding probabilities and the consumption policy functions, update the wage policy functions

- Using the policy functions computed in the previous step, compute the distribution of agents across states, Ω.

- Check that asset markets clear and the government budget holds

- If not, update the guess and repeat

Along the transition path, when solving for the economy's response to a single unexpected aggregate productivity shock, I employ the sequence space Jacobian method proposed by Auclert et al. (2021). Using this approach speeds up the solving process by a factor of 20, compared to traditional methods of gradient descent.

I calculate the earnings procyclicality measures using a non-stochastic simulation approach. I