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Hiermit erkläre ich, dass ich die Arbeit selbstständig angefertigt und die benutzten Hilfsmittel vollständig und deutlich angegeben habe.

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Preface

This dissertation consists of three self-contained chapters. The common theme connecting these chapters is the focus on how the labor market affects inequality in the economy. The first chapter studies how changes in the unemployment insurance system impact labor market inequality in the presence of endogenous labor force participation. In the second chapter, biased labor market expectations discourages individual asset accumulation contributing to wealth inequality. Diverging supply of high-skilled workers influencing the firm distribution and fostering wage inequality across Germany is the topic of the third chapter. The following provides a short summary of each chapter.

Chapter 1: Unemployment Insurance Reforms in a Search Model with Endogenous Labor Force Participation
This chapter is joint work with Andreas Gulyas[1] and Ioannis Kospentaris[2].
We develop a life-cycle search model with a labor force participation decision of workers, job-to-job transitions, endogenous separations and job creation to study unemployment insurance (UI) reforms. We evaluate the impact of two reforms: a duration extension to 99 weeks, and an equally expensive benefit increase. Both reforms lead to a decrease in the employment to population ratio, but leave the labor force participation rate and labor productivity roughly constant. The duration extension yields a higher unemployment rate compared to the benefit increase. Older workers respond more to UI reforms than prime-age and young workers, diminishing their labor market prospects the most. Workers' participation decisions, job-to-job transitions and separations account for a substantial part of the economy's response to UI reforms.

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Chapter 2: The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare

This chapter is joint work with Almut Balleer[3], Georg Dürnecker[4], and Susanne Forstner[5].

Idiosyncratic labor market risk is a prevalent phenomenon with important implications for individual choices. In labor market research, it is commonly assumed that agents have rational expectations and, therefore, correctly assess the risk they face in the labor market. We analyze survey data for the U.S. and document a substantial optimistic bias of households in their subjective expectations about future labor market transitions. Furthermore, we investigate the heterogeneity in the bias across different demographic groups and find that high-school graduates tend to be strongly over-optimistic about their labor market prospects, whereas college graduates have rather precise beliefs. In the context of a quantitative heterogeneous agents life cycle model, we show that the optimistic bias has a quantitatively sizable negative effect on the life cycle allocation of income, consumption and wealth and implies a substantial loss in individual welfare compared to the allocation under full information. Moreover, we establish that the heterogeneity in the bias leads to pronounced differences in the accumulation of assets across individuals, and is thereby a quantitatively important driver of inequality in wealth.

Chapter 3: Non-Convergence of East German Wages: Effects of Skill Shortage on Firm Organization

Why have average labor productivity and wages not converged between East and West Germany after reunification? Documenting a diverging relative supply of high-skilled workers, I propose a new explanation for this puzzle: In the presence of fewer high-skilled workers, East German firms operate under a different organization of production, stay smaller, are less productive, and pay lower wages. Exploiting rich, administrative datasets, I document a positive relation between the size and the share of high-skilled workers in an establishment, as well as positive semi-elasticicities regarding wages for both worker types and regions controlling for observables. Using a general equilibrium model with large firms operating in a frictional labor market, over 26% of the wage gap after controlling for on worker and job characteristics between East and West Germany in 2015 can be explained by the lower relative supply of high-skilled workers. The model also predicts that output would increase by 20% if East Germany had the same relative supply of workers as West Germany.

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Chapter 1

Unemployment Insurance Reforms in a Search Model with Endogenous Labor Force Participation

This chapter is joint work with Andreas Gulyas and Ioannis Kospentaris.
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1 Introduction

The provision of unemployment insurance (UI) benefits constitute the most prominent policy to insure workers against joblessness. The effects of UI benefits have been studied extensively in labor economics, documenting that high levels of UI may worsen workers' job-finding prospects.[1] A recent literature explicitly models the firms' job creation response to UI extensions and uses structural models to obtain reliable counterfactual policy results.[2] The structural approaches have so far abstracted from workers' labor force participation decisions, as well as job-to-job transitions, which may have important implications for the analysis of UI reforms. On the one hand, more generous UI might improve workers' labor market outcomes as it incentivizes workers to stay in the labor force longer. On the other hand, firms may respond by creating fewer vacancies, which might be detrimental for labor productivity as fewer workers transition to high productivity jobs.

To address these challenges, we build upon Menzio, Telyukova, and Visschers (2016) and develop a life-cycle search model with an endogenous labor force partici-

[1] See, among others, Schmieder and von Wachter (2016) and Tatsiramos and Van Ours (2014) for recent surveys of the microeconomic literature on the effects of UI benefits and Chodorow-Reich, Coglianese, and Karabarbounis (2019), Hagedorn, Karahan, Manovskii, and Mitman (2013), Hagedorn, Manovskii, and Mitman (2015), and Johnston and Mas (2018) for the aggregate effects.

[2] See Krause and Uhlig (2012), Nakajima (2012), Mitman and Rabinovich (2019), Hartung et al. (2020), and Rujiwattanapong (2021).

pation decision of workers. This extension makes this the first model in the literature featuring endogenous job creation by firms and job-to-job transitions in a three state model of the labor market. This unique combination allows us to comprehensively study the effects of an UI extension to 99 weeks and an equally expensive increase in UI benefits of 17.6%, while holding eligibility duration fixed at 6 months. We find that both UI reforms leave the labor force participation rate (LFPR) and labor productivity roughly unchanged, but moderately reduce employment and GDP, and increase unemployment. Inspecting the model's mechanisms reveals that these effects are mostly driven by changes in the separation rate and flows in and out of the labor force. The main difference between the two reforms is that the UI extension has a larger impact on the unemployment rate, because fewer unemployed workers drop out of the labor force. Moreover, the life-cycle structure of the model allows us to study how workers of different ages respond to more generous UI benefits and find that older workers respond more than prime-age and young workers. This implies that states with older populations, such as Florida, may have significantly different responses to UI extensions than states with more young workers, such as Utah.

Our main contribution is to show that disregarding the effect of flows in and out of the labor force, job-to-job transitions, and endogenous separations implies a significant bias in the analysis of UI reforms. Typically, in search models, more generous UI leads workers to become "pickier" and search for more productive jobs, which increases labor productivity. In our model with on-the-job search, labor productivity slightly declines because fewer employed workers move on to more productive jobs due to depressed job-to-job transitions. In addition, we show that the changing labor force participation decisions and increased separations in response to more generous UI benefits account for the majority of the total unemployment increase. In conclusion, we argue that omitting the flows in and out of the labor force and job-to-job transitions as well as treating separations as exogenous would lead to a biased assessment of the effects of UI reforms.

In our model, workers are heterogeneous in home production, which is subject to idiosyncratic shocks. These shocks capture in reduced form all changes to the relative return of market work compared to home production, such as child and family caring responsibilities, health, and disability shocks. In addition, workers age stochastically through a life-cycle, which also affects the value of home production. Non-employed workers choose whether to join the pool of unemployed or to drop out of the labor force. The unemployed give up a fraction of their home production in exchange for a higher job contact rate. To account for the large fraction of hires from out of the labor force, we assume that non-participating workers still contact jobs, but at a lower rate.[3] Successful matches start out with unknown productivity, which has to be learned

[3]In CPS, 38.3% of new hires every month are from workers coming from out of the labor force.

over time. Employed workers engage in job search and transition to more productive matches over the life-cycle.

On the other side of the market, firms decide how many and what type of vacancies to open. Vacancies differ in the type of workers they hire and the promised utility they offer, which gives rise to a segmented labor market. In each submarket, the frictional meeting process is modeled with a constant returns to scale matching function. Workers choose which type of vacancy to search for. This decision entails a trade-off, as high utility jobs attract more applicants but feature a lower job-finding probability. Workers with high home production or in high productivity matches search in submarkets with high promised utility but low job-finding rate. Finally, matches can be either endogenously or exogenously dissolved.

We calibrate the model targeting the average monthly labor market flows and the LFPR over the life-cycle, in addition to the job tenure distribution. The tenure distribution provides information about the distribution of match-specific productivity, in addition to the labor force attachment of workers. This creates a tension in the calibration: the monthly movements in and out of the labor force are very large, while there are many workers in jobs with long tenures. To account for the frequent movements in and out of the labor force requires a very volatile home production process, which would contradict the large mass of persistently employed workers. Our model overcomes this challenge with the interaction between home production and match-specific productivity. Workers in high quality matches have a higher home productivity threshold for separations and remain employed for long periods of time. At the same time, the home production process has enough volatility for the model to match *all* labor market flows perfectly. This is not a trivial outcome in search models with labor force participation, as typically these models are not flexible enough to match all flows.[4]

Any framework aiming to understand the aggregate effects of UI reforms should take into account the differences across workers' labor market attachment, since this heterogeneity is likely to affect the impact of UI policies. For example, Lalive (2008) and Tatsiramos (2010) have shown that old workers use UI as a bridge to retirement, and thus might react differently to UI changes compared to prime age workers. Similarly, workers with strong labor market attachment, such as prime-age workers, may respond less strongly to an increase in UI benefits compared to young and older workers with lower attachment.[5] To gauge the model's ability to capture these aspects of

[4]For example, Garibaldi and Wasmer (2005) report that their model falls short in accounting for the magnitude of the UN and NU flows. Krusell et al. (2011) also report that the UN flow is too small and the UE flow is too large in their model compared to the data. Similarly, the model in Cairo et al. (2020) does not have enough degrees of freedom to account for the magnitude of several observed flows.

[5]For another example of differential attachment, Mankart and Oikonomou (2017) show that secondary earners change their behavior more often than primary earners over the business cycle.

worker heterogeneity, we examine its performance with respect to two sets of untargeted moments: the labor market flows over the life-cycle, and workers' four-month labor market histories identified from the CPS panel dimension (based on Kudlyak and Lange, 2018 and Hall and Kudlyak, 2019). We show that the labor market flows over the workers' life-cycle and the four-month labor market histories predicted by the model are close to the empirical ones. This shows that the model is consistent with rich heterogeneity in the labor market attachment of various workers, which makes it a suitable framework to study UI reforms.

We use the model to study the effects of a permanent UI benefits extension to 99 weeks and contrast this reform to an equally expensive 17.6% increase of UI benefits while holding eligibility duration fixed. The 99 weeks extension leads to an increase in the unemployment rate by 12%, or a 0.7 percentage point increase, and to a modest decline in the employment to population ratio by 0.8%. The declining employment rate in addition to a slight decrease in labor productivity yields a decrease in GDP by 0.8%. Which mechanisms account for these changes in the labor market? The increase in the unemployment rate is driven mostly by changes in the separation rate and the flows in and out of the labor force, as opposed to changes in the job-finding probability.[6] Thus, our exercise highlights the importance of separations for the effects of UI reforms, in line with recent empirical evidence. Hartung et al. (2020), studying a cut in UI eligibility duration in Germany, show that three quarters of the decline in the unemployment rate are due to lower separation rates into unemployment. Similarly, Jäger et al. (2019) find that an extension of UI benefits in Austria raised separations by 27% over its four year implementation.

We further show that the UI extension leaves the LFPR virtually unchanged. This seems counterintuitive at first, because it is often argued that more generous UI benefits incentivize workers to stay longer in the labor force. Our model indeed estimates that flows from unemployment to out of the labor force (UN) would decline by 14%, consistent with the empirical findings of Rothstein (2011) and Farber and Valletta (2015). The UI reform nevertheless leaves the LFPR unchanged. This occurs because the reservation productivity for staying in a match increases, which in turn increases the separation rate. Together with the reduced job-finding rates, this counteracts the decline in the UN rate and leaves the LFPR unchanged.

We contrast this change in the UI system with an equally expensive increase in UI benefits by 17.6%, holding UI eligibility duration constant at 6 months. This reform leads to similar employment effects, but to a 3% smaller increase in the unemployment rate (9% compared to 12%). The reason for this difference is that the UN flow declines more for the duration extension than for the benefit increase. This is driven by the

[6]These findings also echo the results of Elsby et al. (2009) and Elsby et al. (2015) who highlight the importance of the separation and participation margin, respectively, for unemployment fluctuations.

unemployed workers who drop out of unemployment once benefits run out. Finally, the effects of both UI reforms on GDP and labor productivity are similar. With both policies, job-to-job transitions decline, implying fewer transitions to highly productive matches, which slightly pulls average labor productivity down. Together with the lower employment rate, this leads to a decline in GDP of about 0.8%.

Finally, using our model, we show that it is quantitatively important to account for the changes in *all* labor market flows as well as the life-cycle dimension to comprehensively understand the effects of UI benefit reforms. First, a decomposition of the model forces yields that the labor force participation decision alone accounts for 50% of the overall unemployment response. Second, we find that old workers respond much more than young and prime-age workers to changes in UI provision. Importantly, this result is consistent with the empirical evidence provided by Michelacci and Ruffo (2015) who, using SIPP data, find that the unemployment rates of older workers are more responsive to UI changes. Although we make no claims about welfare, we believe that it is important to study the positive effects of more generous UI policies, as the policy debate often centers around the effects of these reforms on (un)employment and output.[7] To be specific, the often heard arguments that more generous UI benefits pull workers into the labor force and improve productivity do not hold in our setting.

This paper contributes to two strands of literature. The first studies the aggregate effects of UI reforms. Recent contributions, among many others, include Chodorow-Reich et al. (2019), Hagedorn et al. (2013), Hagedorn et al. (2015), and Johnston and Mas (2018). Most closely related are Hartung et al. (2020), Krause and Uhlig (2012), Mitman and Rabinovich (2019), Nakajima (2012), and Rujiwattanapong (2021) who study the effects of UI reforms using equilibrium search models.[8] An important difference with our work is that we consider a model with a labor force participation choice, as well as job-to-job transitions. For example, in a model without on-the-job search, Acemoglu and Shimer (1999) show that more generous UI makes workers pickier and may increase labor productivity. We show that including job-to-job transitions counteracts this channel. More generous UI reduces job-to-job transitions, which leads fewer workers climbing up the job ladder to more productive jobs, ultimately slightly lowering labor productivity. Similarly, flows in and out of the labor force account for half of the unemployment response to more generous UI.

Second, we contribute to the literature that develops search and matching models with an out of the labor force state, in the tradition of Pries and Rogerson (2009) and Garibaldi and Wasmer (2005). Compared to Krusell et al. (2010, 2011, 2017), we

[7] The equilibrium of our directed search model is efficient, therefore it is not well suited for welfare comparisons.

[8] Also related is the work of Costain and Reiter (2008) who highlight the link between labor market fluctuations and the responsiveness of unemployment to changes in UI benefits.

endogenize the job creation decision of firms, making our model more suitable for the study of UI reforms. Cajner et al. (2021) enrich the framework of Krusell et al. (2010, 2011) with the life-cycle dimension; similar to us, they find that the unemployment rate of older workers changes more when UI benefits increase. Compared to Haefke and Reiter (2011) and Cairo et al. (2020), our model is flexible enough to match all the labor market flows perfectly and includes job-to-job transitions, although they go beyond our paper in studying the model's cyclical properties. Finally, we complement the work of Kudlyak and Lange (2018) and Hall and Kudlyak (2019) who exploit the panel dimension of CPS to identify heterogeneity in labor force profiles across workers. In our model, this heterogeneity is driven by economic choices, and, to the best of our knowledge, we are the first to compare model-generated four-month labor force histories with CPS data.

The rest of the paper is organized as follows. The next Section describes the model framework. Section 3 lays out the identification strategy and Section 4 presents the calibration results along targeted and untargeted moments. In Section 5, we present the effects of more generous UI schemes on labor market stocks and flows. Section 6 concludes. Finally, the appendix presents multiple robustness exercises with respect to different parameterizations, as well as the full transition path of the economy after the UI reforms.

2 The Model

In this Section we lay out our model of worker flows over the life-cycle. The model builds on the directed search framework of Menzio and Shi (2011) and Menzio, Telyukova, and Visschers (2016). Workers go through a life-cycle and decide whether to participate in the labor market. They trade off the value of home production in exchange for market work. Eligible unemployed workers receive unemployment benefits, which expire after some time. The labor market is frictional and segmented in submarkets. Firms choose how many and what type of vacancies to offer, and workers direct their search towards these type of vacancies.

2.1 The Environment

Time is discrete and the economy is populated with a unit mass of workers and a positive mass of firms to be determined in equilibrium. Workers stochastically age through a life-cycle, which is modeled as A distinct stages of aging. Each period, a worker of age a reaches the next stage $a+1$ with probability p_a. After they aged through the last stage, workers exit the model and are replaced by an entering cohort of young agents.[9] In addition to age, workers are also heterogeneous in their home production. Home production is comprised of an idiosyncratic component h, which is subject to shocks, as well as an age-specific component $\bar{h}(a)$. In contrast to most of the search literature, workers' participation in the labor market entails an economic choice. They trade off their home production with the opportunity to earn a market wage.

The level of home production in our model should be thought of as the value of non-participation in the labor market relative to market work. Therefore, it is a reduced form way of capturing all relevant reasons for not participating in the labor market. It comprises the value of goods and services produced at home, such as food preparation, child care, elderly care, in addition to the value of leisure. But it also includes other important dimensions such as health shocks, or the value of getting education. Our goal is not to explicitly model the different reasons why workers do not participate in the labor market, but rather build an equilibrium framework where worker flows are generated by economic decisions of agents.

The modeling details of UI benefits follow Mitman and Rabinovich (2015). The standard duration of unemployment benefits is six months in the United States. To obtain tractability, we model this in a stochastic fashion, assuming that UI benefits may expire at each month with a certain probability chosen to match the average duration of six months. Only workers with a previous employment spell receive unemployment benefits, whereas workers rejoining the labor force are not eligible. Finally, in the main body of the paper, we abstract from modeling the government's budget constraint to keep the model computationally tractable.[10] In appendix D, we show that introducing a tax on worker-firm matches to finance UI expenditure changes neither the baseline model results, nor the results from the policy reforms. The reason behind this is that UI expenditure are below 0.4 percent of GDP in the data, thus the tax rate required to finance it is too small to quantitatively affect our results.

Periods are subdivided into six stages: realization of shocks, separation, matching, search, learning, and production. In the beginning of the period, all innovations to home productivity and aging shocks, as well as the expiration of unemployment benefits are realized.

In the separation stage, these shocks might trigger endogenous separations for employed individuals. In addition, matches dissolve exogenously with probability δ_0.

[9] The assumption of stochastic aging greatly simplifies the computational burden of the model. Since agents are risk-neutral, the assumption of stochastic aging compared to deterministic aging is inconsequential.

[10] Adding a government budget constraint to the model would impose non-trivial computational burden, since it requires solving a fixed point problem for taxes.

The period continues with the matching stage. Workers participating in the labor market have the opportunity to search with a probability that depends on their employment state. For the unemployed this probability is λ_u, whereas employed workers engage in on-the-job search with probability λ_e. To account for the large amount of worker flows from out of the labor force directly to employment, we also allow workers not participating in the labor force to take part in the matching process with a probability λ_o.[11] We label unemployed workers active searchers, and workers out of the labor force passive searchers.

The labor market is frictional and search is a time-consuming process. While workers are unemployed, they have to forgo a fraction $1 - \phi$ of their flow utility from home production to engage in active job search. Workers are directing their search towards specific submarkets indexed by (x, a, h). These submarkets differ in terms of the meeting probability and the promised value of the job to the worker x. In submarket (x, a, h), firms offer workers of type (h, a) a contract with promised life time utility x to the worker.

Workers are able to choose the submarket in terms of promised life time utility x, but are forced to search in the submarket for their respective type.[12] Intuitively, submarkets with high promised life-time utility will be visited by more workers. As a consequence, each submarket (x, a, h) will have a different labor market tightness, as defined by the ratio of vacancies to job seekers, i.e. $\theta(x, a, h) = v(x, a, h)/u(x, a, h)$. Of course, the composition of job seekers varies across submarkets, as some submarkets are populated by employed, unemployed or workers out of the labor force. Conditional on having the opportunity to search, a worker visiting submarket (x, a, h) faces a probability of meeting a vacancy of $p(\theta(x, a, h))$.

Profit maximizing firms also choose how many vacancies to open in each submarket. Maintaining a vacancy costs k units of output per period. A vacancy in submarket (x, a, h) meets a worker with probability $q(\theta(x, a, h))$, where both $p()$ and $q()$ are twice differentiable, strictly increasing and strictly concave functions such that $q(\theta) = p(\theta)/\theta$. After a successful meeting, nature draws a match specific productivity z from the distribution $f(z)$. Matches are experience goods, and the idiosyncratic match productivity is unknown to both partners at the beginning. At the end of each matching stage, workers and firms in matches with unknown z learn the productivity with probability α. The assumption that matches are experience goods is grounded in the observation that many matches are dissolved within a few months, and that most jobs have a specified trial period.[13]

[11] In CPS, 38.3% of all new hires involve workers from out of the labor force.

[12] This assumption will guarantee that the equilibrium is block-recursive, which reduces the computational burden of the model.

[13] According to CPS, 23% of employed workers have job tenure less than a year.

After the matching stage, non-employed workers decide whether to actively search and join the pool of unemployed, or to drop out of the labor force. The period concludes with the production stage. Employed workers produce z units of output. Workers outside of the labor force produce according to their idiosyncratic productivity h times their age specific home productivity component $\bar{h}(a)$. Actively searching unemployed workers forgo a fraction $(1-\phi)$ of their home productivity. Additionally, they might be eligible for unemployment benefits of level $\bar{b}$.

As is typical in the literature, we include all workers from 16 to 64 in our analysis. In the United States, most workers become eligible for social security retirement benefits at the age of 62 (French, 2005), which coincides with our latest age group. To capture this, workers in the oldest age group (ages 60-64) are also entitled to a retirement benefit b_R, which is available only if they stay out of the labor force.

2.2 Value Functions

We start with the problem of workers who have the opportunity of searching. These workers face a trade-off between choosing a submarket with a high promised life-time utility but low job-finding rates, or lower paying jobs that are easier to come by. This maximization problem is described in equation (1.1).

$$R(V,a,h) = \max_x p(\theta(x,a,h))\,[x - V] \tag{1.1}$$

The value of search consists of the probability of finding a job $p(\theta(x,a,h))$ times the capital gain from finding a job. This is given by the promised life-time utility x of the job, minus the outside option of the searching worker V, which can be the value of employment or non-employment.

Next, equation (1.2) describes the problem of a non-employed worker in state a,h with unemployment benefits $b \in \{0,\bar{b}\}$, facing the labor force participation decision.

$$N(a,h,b) = \max\{N^u(a,h,b), N^o(a,h)\} \tag{1.2}$$

The worker simply chooses to drop out of the labor force if its continuation value $N^o(a,h)$ is higher than the value of engaging in active job search $N^u(a,h,b)$. These value functions at the beginning of the production stage are presented in equations (1.3) and (1.4).

$$N^o(a,h) = \exp(h+\bar{h}(a)) + b_R \mathbb{1}_{a\geq 60} + \beta\mathbb{E}[N(a',h',0) + \lambda_o R(N(a',h',0),a',h')] \tag{1.3}$$

A worker that is currently not in the labor force enjoys flow utility of $\exp(h+\bar{h}(a))$. Additionally, the oldest workers, for whom retirement benefits are available, receive an additional payoff b_R if they do not participate in the labor force. Beginning of next period, shocks to home productivity and age realize. The expectation is taken over all possible future values of h' and a'. Throughout the paper, we denote all variables in the next period with a prime. Next period, the worker again faces the decision to join or stay out of the labor force. Workers who rejoin the labor force are not eligible for UI benefits, thus the continuation value is the discounted expected value of equation (1.2), with $b = 0$. With probability λ_o she has the opportunity to search next period, which is valued $R(N(a', h', 0), a', h')$. Finally, newly born workers enter the labor market as non-employed and draw home production h from the stationary distribution.

Because unemployed workers have to spend a certain amount of time on search, they only receive a fraction ϕ of their total home productivity $\exp(h + \bar{h}(a))$ as flow payoff. In addition, workers receive unemployment benefits $b \in \{0, \bar{b}\}$, depending on their eligibility status. With probability λ_u, the worker is able to participate in the matching process, which entails a capital gain of $R(N(a', h', b'), a', h')$. Formally, the problem of an unemployed worker is presented below

$$N^u(a,h,b) = b + \phi \exp(h + \bar{h}(a)) + \beta \mathbb{E}\left[N(a', h', b') + \lambda_u R(N(a', h', b'), a', h')\right]. \quad (1.4)$$

Next, consider an employed worker of type (a, h) who is in a match with known quality z at the beginning of the production stage. The joint value of the match for the firm and the workers is given by

$$\begin{aligned} V(a,h,z) &= z \\ &+ \beta \mathbb{E}\left[\max_{d \in [\delta_0, 1]} \left\{ dN(a', h', \bar{b}) + (1-d)\left[\lambda_e R(V(a', h', z), a', h') + V(a', h', z)\right]\right\}\right]. \end{aligned} \quad (1.5)$$

The match produces z units of output. At the beginning of next period, the new values of h' and a' are revealed and the match partners can decide to separate by setting $d = 1$. If the match is neither exogenously nor endogenously dissolved, it continues to the matching stage where the worker gets the opportunity to search with probability λ_e. This opportunity is valued at $R(V(a', h', z), a', h')$. If the search is unsuccessful, the continuation value is $V(a', h', z)$.

Successful matches initially start out with unknown quality z_0. The value of these matches at the beginning of the production stage is given by

$$\begin{aligned} V(a,h,z_0) = \alpha \sum_z V(a,h,z) f(z) \ + (1-\alpha) \Bigg(\sum_z z f(z) + \beta \mathbb{E}\Bigg[\max_{d \in [\delta_0, 1]} \{ dN(a', h', \bar{b}) \\ + \ (1-d)\left[\lambda_e R(V(a', h', z_0), a', h') + V(a', h', z_0)\right] \} \Bigg] \Bigg). \end{aligned} \quad (1.6)$$

Just before production takes place, with probability α the productivity of the match is revealed. With probability $1-\alpha$, the match continues with unknown productivity. In expectation, the match produces $\sum_z zf(z)$ units of output. The continuation value mirrors the one with known match quality.

Free entry on the firm side drives down the firm's expected gain from opening a vacancy in each submarket to its cost k. The gain is given by the job filling probability in the respective submarket, multiplied with the value of the job minus the amount promised to the worker:

$$k \geq q(\theta(x,a,h))\,(V(a,h,z_0)-x)\,. \tag{1.7}$$

This relationship pins down θ and hence the job-finding and job-filling probabilities for all submarkets in all states of the economy. Thus, firms and workers can form expectations about these objects without the knowledge of the distribution of matched and unmatched agents, giving rise to the block-recursive nature of the model (Menzio and Shi, 2011).

With all value functions described, we define the Block Recursive Equilibrium in this environment as in Menzio and Shi (2010, 2011) and Menzio et al. (2016):

Definition 1. *A Block Recursive Equilibrium in this environment consists of a market tightness function θ, value functions V, N, N^u, N^o, a policy function for the participation decision of non-employed workers s, policy functions regarding the market to search in x^u, x^o, and policy functions for the firm-worker match, (d, x^e). These functions must satisfy the following conditions:*

1. *$V, N^u, N^o, N, s, x^o, x^u, x^e, d, \theta$ are independent of the distribution of agents across states.*
2. *θ satisfies the free entry condition $\forall\ (x,a,h)$ in equation (1.7)*
3. *s, x^u, x^o, x^e, d maximize the value functions V, N^u, N^o, N in equations (1.2)–(1.5).*

The next Section discusses the calibration of the model.

3 Calibration

To calibrate the model, we have to specify a distribution of match-specific shocks, a functional form for the matching function, as well as the processes for the age profile and idiosyncratic shocks of home production. First, we assume that match-specific productivity z is drawn from a uniform distribution $\mathcal{U}([-\Delta_z, \Delta_z])$. Second, since the model is formulated in discrete time, we choose to work with the CRS matching function $M(u,v) = \frac{uv}{(u^\gamma+v^\gamma)^{\frac{1}{\gamma}}}$, which yields well-defined job-finding and job-filling

Parameter	Value	Description	Target
α	0.3333	Prob. of learning	Average learning duration of 3 months
β	0.996	Discount factor	5% real interest rate
γ	0.6	Matching function elas.	Literature (see main text)
λ_e	1	Meeting intensity employed	Normalization
p_b	0.8329	Prob. of keeping UI benefits	Average eligibility duration of 26 weeks
p_a	0.0167	Aging Probability	Average lifecyle of 50 years with 10 age groups

Table 1.1: Externally Calibrated Parameters

probabilities between 0 and 1.[14] Third, for the age profile of home production, we assume a linear spline with three different regimes:

$$\bar{h}(a) = \begin{cases} \frac{h_2-h_1}{a_1}(a-15)+h_1 & a \in [15, a_1] \\ \frac{h_3-h_2}{a_2-a_1}(a-a_1)+h_2 & a \in (a_1, a_2] \\ \frac{h_4-h_3}{64-a_1}(a-a_2)+h_3 & a \in (a_2, 64] \end{cases}$$

These regimes capture the behavior of labor force participation over the life-cycle: it increases for young workers, plateaus during prime age, and decreases as workers get older. The process is characterized by six parameters: a_1 and a_2 are the age cutoffs at which the home production regime changes, while $h_1 - h_4$ determine the unconditional levels of home production at ages $15, a_1, a_2$, and 64, respectively. Finally, the process for idiosyncratic home production shocks, h, follows a stochastic process. Each period, with probability p_h, agents draw a new h' from the distribution $\mathcal{U}([h-\Delta_h, h+\Delta_h])$. Thus, p_h governs the frequency, and Δ_h the magnitude of home production shocks. With probability $1-p_h$ the worker continues with their old home production h.[15] We discretize the process for h using the method from Tauchen (1986).[16]

We set a period in the model to be one month. Several model parameters are set exogenously and their values are presented in Table 1.1. The discount factor β is set to 0.996, consistent with a 5% annual interest rate. Moreover, we set the elasticity of the matching function, γ, to 0.6, which lies between the estimates reported by Den Haan et al. (2000) and Hagedorn and Manovskii (2008). We normalize the meeting intensity λ_e of employed workers to unity; we calibrate endogenously the meeting intensities

[14]We use u to denote the measure of job seekers in a particular submarket. This may consist of employed, unemployed or individuals out of the labor force.

[15]We have calibrated the model with an AR(1) process for the home production shocks and the results are very similar. As we explain later, it is important that the home production process has persistence; simple iid shocks would not allow us to match the labor market flows.

[16]Since we are modeling a unit root process, we have to impose ex ante bounds for the values of h in the calibration process. We assume that h can take values in a $[-2, 2]$ grid. We assign all probability mass falling outside the grid to the boundaries.

of workers who are unemployed and out of the labor force. The monthly probability of a worker keeping UI benefits p_b is set to 0.8329 which yields an average eligibility duration 26 weeks in the model, the standard UI duration in the US. Moreover, we choose to have 10 age groups and an average career length of 50 years. This implies an average group length of 5 years, which we achieve by setting the aging probability p_a equal to 0.0167. Finally, we set the probability of learning the quality of a firm-worker match to one third per period. This implies a modest level of learning frictions, since workers and firms learn their match quality in three months on average, very close to the parameterization of Menzio et al. (2016). In the appendix Section G, we show that our results also hold for different parameterizations. We conduct a sensitivity analysis with respect to both higher and lower levels of the learning speed α and the elasticity of the matching function γ.

The remaining 15 parameters are calibrated internally. We choose a set of identifying moments from US data to inform these model parameters. To begin with, the choice of the identifying moment for the flow value of unemployment benefits $\bar{b}$ is straightforward. We use the the long run average of the ratio of unemployment benefit expenses over GDP from 1982 to 2016 in the US, reported by the OECD, as a target for the generosity of unemployment benefits.[17]

For most of the remaining identifying moments, our main data source is the Current Population Survey (CPS) obtained from Integrated Public Use Microdata Series (IPUMS) from 1982 to 2018.[18] Following Kudlyak and Lange (2018), we restrict our attention to workers that have either four or eight interviews in CPS.[19] The calculation of labor force histories is possible only for these workers and we want to use the same sample for both targeted and untargeted moments. We consider workers between 16 and 64 and we treat the data set as a large cross-section. That is, we pool all observations together before computing averages.

The identification strategy for the parameters describing labor market frictions is standard. The transition rates between employment, unemployment, and out of the labor force (OLF), as well as the job-to-job transition rate inform the search friction

[17] According to the OECD Public Unemployment Spending series, spending on unemployment benefits accounts for 0.4% of US GDP. We also consider an alternative target, where we exclude capital income from GDP, since capital is missing in our model, and target UI expenditures over labor income instead. This moment choice is inconsequential for our results, see appendix G.

[18] The IPUMS database is made available by the Minnesota Population Center. Using the CPS data from IPUMS compared to NBER has an important advantage: individual ids are fully linked over time. They are meticulously constructed by Rivera Drew et al. (2014) with a procedure that improves upon the standard procedure of Madrian and Lefgren (2000) usually employed in the literature. As a result, all variables of interest are harmonized over time. We also performed the standard sanity test of checking whether sex, race and age are consistent within individual records. There were few ids that did not have consistent demographics, which we dropped from the sample.

[19] Using workers with at least two consecutive interviews in CPS yields almost identical labor market flows.

Transition Rates CPS 1982–2018			Benefits OECD and March CPS 1982-2018			Tenure Distribution CPS Job Tenure Suppl.			LFPR CPS 1982–2018		
Flow	Data	Model	Target	Data	Model	Years	Data	Model	Age	Data	Model
JJ	0.021	0.021	b/GDP	0.004	0.004	≤ 1	0.229	0.259	15–19	0.460	0.463
EU	0.013	0.013	b_R/GDP	0.072	0.072	$(1,3]$	0.227	0.188	20–24	0.754	0.751
EN	0.024	0.024				$(3,9]$	0.273	0.280	25–29	0.830	0.845
UE	0.238	0.234				> 9	0.271	0.273	30–34	0.834	0.852
UN	0.214	0.208							35–39	0.840	0.845
NE	0.063	0.063							40–44	0.847	0.840
NU	0.039	0.038							45–49	0.835	0.816
									50–54	0.796	0.789
									55–59	0.709	0.740
									60–64	0.518	0.534

Table 1.2: Empirical Moments and Model Fit

parameters λ_u and λ_o, the flow cost of vacancy creation k, the exogenous separation rate δ_0, and the cost of active job searching $1-\phi$.

These transition rates also inform the two parameters characterizing the home production process: p_h, capturing the likelihood of a shock, and Δ_h, capturing the shock's magnitude. Intuitively, the mapping between the data moments and the model parameters works as follows. The flows from unemployment and OLF to employment pin down λ_u and λ_o, respectively. The cost of vacancy creation, k, determines the overall scale of job-finding probabilities from all states; since we normalized λ_e to unity, the remaining job-to-job transition rate informs k. δ_0 is linked to the flow from employment to unemployment. The cost of active searching, $1-\phi$, directly affects the transition from OLF to unemployment. Finally, the flows from employment and unemployment to non-participation inform the home production process: the former speaks to the magnitude of shocks, since large shocks are required to move employed workers to the OLF state instead of unemployment. The volatility of the process affects the latter flow, as frequent shocks drive unemployed workers OLF before they find a job and transition to employment.

To identify the six parameters governing the home production profile over the life-cycle, we target the labor force participation rate for ten age groups over the life-cycle. It is important to notice that we do not include the age profiles for any transition rates in the calibration targets. On the contrary, the predictions of the model regarding flows over the life-cycle will be used to gauge model performance.

To pin down the level of retirement benefits, b_R, we use data from CPS's Annual Social and Economic Supplement (ASEC; commonly referred to as the "March CPS"). This data provides information regarding the respondent's retirement income received from all available sources during the past year. The statistic we use as a target is average retirement payment to workers between 60 and 64 over GDP per person.[20] The average of this series from 1982 to 2018 is 7.2%, a target matched exactly by our model.

The only parameter left to pin down is Δ_z, which governs the dispersion in match specific productivity. To identify Δ_z, we target the job tenure distribution, which we compute using the CPS Job Tenure supplement, also available in IPUMS.[21] The job tenure distribution is informative about the match-specific productivity distribution because the survival probability of a match strongly depends on z. Workers in low z matches have a higher probability of moving to unemployment, looking for another job or even leaving the labor force after learning the match productivity. Therefore, the dispersion of match specific productivities affects the fraction of jobs surviving over time and consequently, the tenure distribution informs the range of shocks Δ_z. A similar identification strategy has been applied in Menzio and Shi (2011). The values of all empirical calibration targets are summarized in Table 1.2.

4 Results

4.1 Worker and Firm Behavior

In this Section, we provide intuition for worker and firm behavior in equilibrium. Figures 1.1, 1.2 and 1.3 contain various pieces of relevant information across three specific age groups: young, prime-age and old workers. These categories correspond to groups 1, 5 and 10 of the ten age groups we used to calibrate the model. In appendix B, we provide the results for all age groups. An important result is that workers of different ages have different behavior; the decision rules, however, have the same qualitative features across age groups, and we start with those.

We explain the choices of non-employed workers in Figure 1.1. First, there are two thresholds, h_b and h_n, above which eligible and non-eligible non-employed workers, respectively, drop out of the labor force (column 1 of Figure 1.1). For values of home production above these thresholds workers prefer to stay OLF, but they accept employment opportunities when they arise, generating NE transitions. These workers prefer to enjoy the full value of their home production over higher future job-finding rates. Second, for values of home production lower than the h_n threshold, workers join the labor force and actively look for jobs. When OLF workers are hit by shocks driving them below this threshold, they perform a NU transition; symmetrically, when non-

[20] We compute the average retirement payment not conditioning on retirement status.

[21] The Job Tenure supplement was conducted in 1983, 1987, and every two years from 1996 to 2018. We compute the tenure moments by pooling all observations and treating it as a large cross-section, similar to what we did with the monthly CPS.

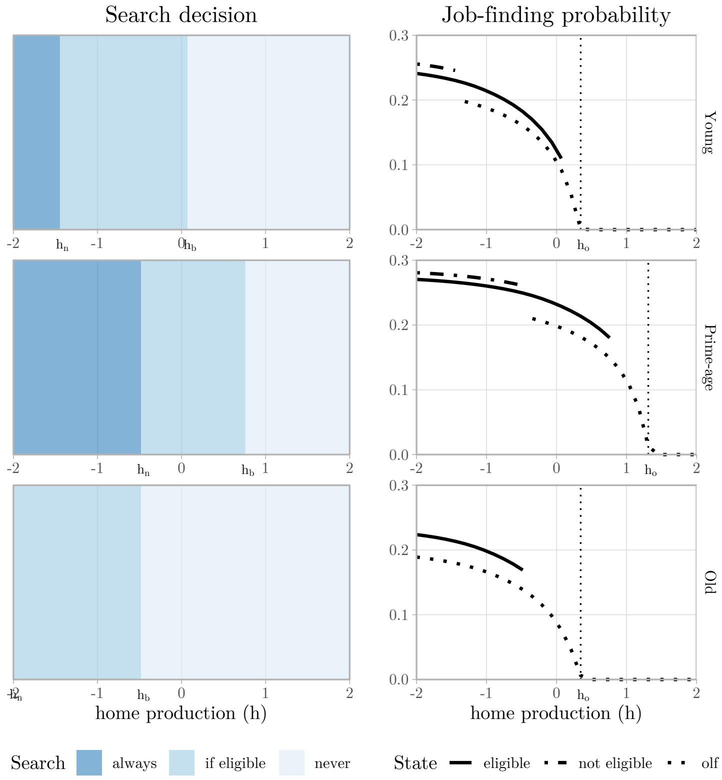


Figure 1.1: Search decision and job-finding probability for different age groups of non-employed workers.

eligible unemployed workers are hit by shocks driving them over h_n, they perform a UN transition.

Moreover, there is a home production threshold h_o above which the probability of finding a job is zero (column 2 of Figure 1.1). Workers with these home production levels require levels of promised utilities which no firm is willing to offer; these workers stay jobless and inactive. Finally, job-finding rates are decreasing in home production; here is the intuition for that. Workers have to be compensated with at least the value of their outside option in equilibrium, otherwise they would not accept the job (see equation 1.1). This implies that the higher the level of a worker's home production, the higher has to be the promised utility the firm offers to the worker. At the same time, free entry of firms implies that firms have to be indifferent between submarkets (see equation 1.7). This means that in submarkets in which they offer high promised utilities, firms have to be compensated with higher vacancy filling rates. To achieve this outcome, firms open less vacancies in submarkets featuring workers of high home production. Put differently, tightness and job-finding probability is a decreasing function of home productivity, as can be seen in column 2 of Figure 1.1.

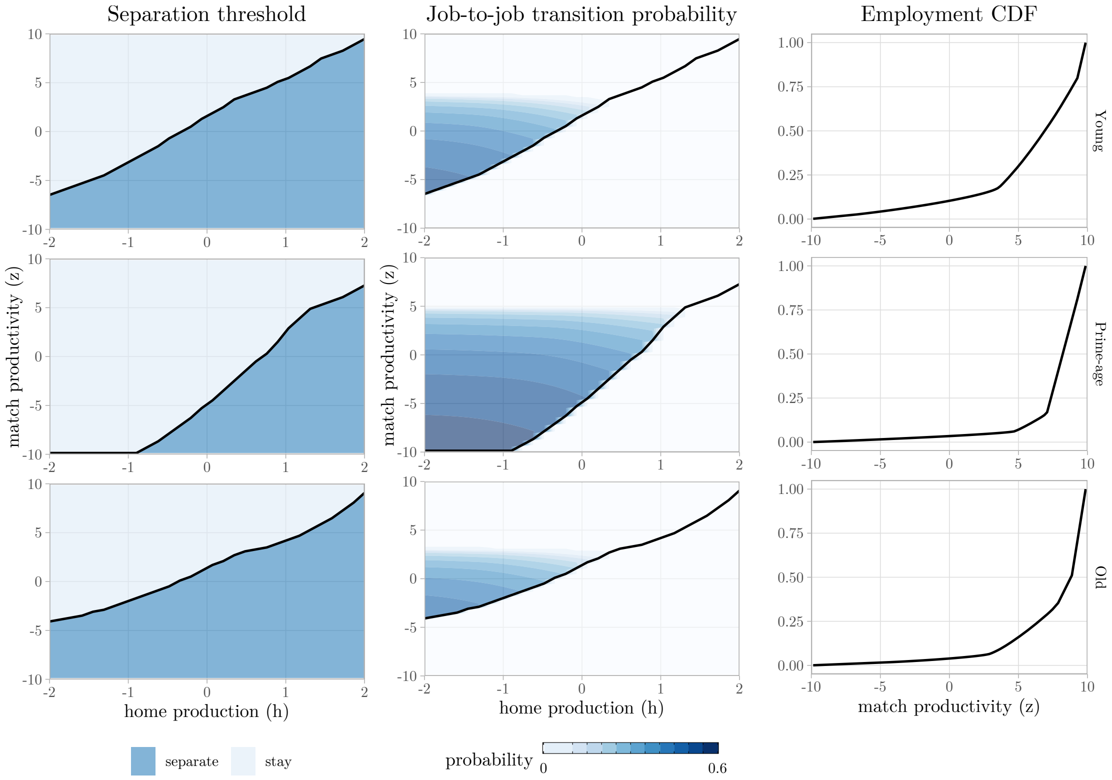


Figure 1.2: Separation threshold, job-to-job transition probability and employment CDF for different age groups of employed workers.

This argument also explains why firms open less vacancies for unemployed workers who receive benefits relative to those who do not receive benefits.[22]

Next, we explain the behavior of employed workers in Figure 1.2. An important aspect of the model for these workers is the interaction of match-specific and home production shocks. This interaction is manifested in how employed workers endogenously separate from jobs: as can be seen in column 1 of Figure 1.2, there is a match-specific productivity threshold $\underline{z}(h)$ which is increasing in the worker's home production level. In other words, employed workers with high home production levels stay employed only if they are employed in matches with high match-specific productivity. The existence of match-specific productivity implies a natural persistence mechanism in the model: workers in high quality matches are "insulated" from home production shocks and remain employed for long periods of time. On the other hand, workers in low quality matches may quit when hit by a relatively small home production shock and immediately try to find a new job. This heterogeneous behavior along the match-specific productivity dimension helps the model generate both a persistent state of employment with many long-tenure matches and many high-frequency worker movements in and out of employment.

[22] Since workers OLF have the same outside option as non-eligible unemployed workers, they choose the same submarket with the same tightness. The difference in job-finding probabilities in column 2 of Figure 1.1 arises only due to the different meeting intensities $\lambda_u > \lambda_o$.

The interaction between match-specific productivity and home production shocks is also crucial for the job-finding rates of employed workers, as column 2 of Figure 1.2 makes clear. Naturally, job-finding rates are decreasing in home production due to the logic we outlined for non-employed workers.[23] They are also decreasing in match-specific productivity, up to a point at which employed workers stop searching because the promised value in their current job is higher than the expected value of a new match. An implication of this is that most employed workers are in high productivity matches, as shown in column 3 of Figure 1.2. Here is the intuition for why job-finding rates for employed workers are decreasing in match-specific productivity. Workers employed in matches of low productivity are eager to leave their jobs for better ones. Therefore, they search in submarkets with higher job-finding rates and lower promised values compared to workers in high value matches who are pickier. Finally, this mechanism generates a negative correlation between job-tenure and job-to-job transitions in the model.

So far we have abstracted from the effect of aging on labor market behavior; however, as workers become older, their labor market behavior changes. There are two main forces that differentiate the behavior of younger and older workers compared to the prime-age ones. First, due to the U-shape of the age-specific part of the home productivity process, young and old workers have higher levels of home production. This, as a result, lowers their labor force attachment. Second, as workers age, the expected remaining duration of their lifetime becomes shorter. Since the exogenous probability a match will dissolve is higher, the value of matching with an older worker is lower for the firms. This force reduces the job-finding rate of old workers, lowering their low labor force attachment even more.

The effects of these two forces can be seen in both Figures 1.1 and 1.2. Focusing on non-employed workers, the home production thresholds h_o, h_b and h_n first increase, and then decrease again, mirroring the U-shape home production profile. In other words, young and old workers with only very low levels of home production stay in the labor force, especially if they are not eligible for UI. Notice that the threshold for non-eligible workers, h_n, moves more than the threshold for the eligible ones, h_b. Actually, the threshold h_n disappears for older workers, implying that they participate in the labor force only if they are eligible for UI and retirement benefits (workers of age 60-64 in the model are entitled to retirement benefits if they stay out of the labor force; see equation 1.3). Due to shorter expected duration of a match, benefits become more important for the decision to stay in the labor force. This is consistent with the evidence that older workers may use UI benefits as a bridge to retirement; see Lalive (2008) and Tatsiramos (2010). Moreover, older workers that are not eligible for

[23] In addition, higher home production lowers the job-finding rate of employed workers because it raises the likelihood of *future* separations.

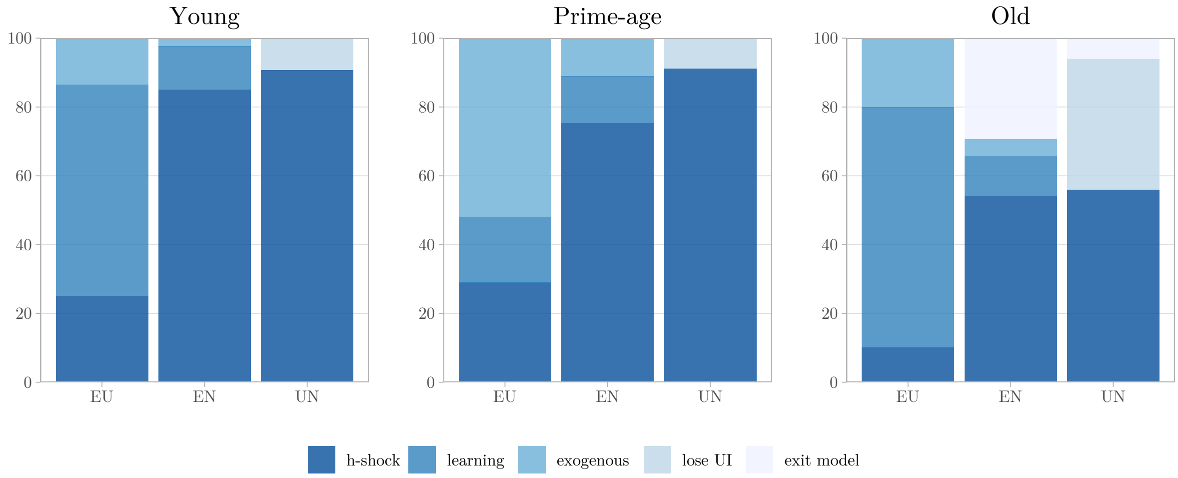


Figure 1.3: Decomposition of flows for different age groups across various model channels.

UI still have a strong incentive to stay out of the labor force to enjoy the retirement benefit. As a result, the h_n shift is more pronounced for old workers. For young workers, participating in the labor force has relatively high returns due to potential movements up the job ladder, while old workers do not have the time to wait for those.

Turning to Figure 1.2, young and old employed workers are pickier than prime-age ones. Their age-specific home production levels are higher, implying a higher reservation match productivity. Moreover, older people have lower job-to-job transition probabilities, since the expected value of a match is lower. Finally, with respect to the employment CDF, it is clearly visible that the median match productivity increases by age. Since good matches need time to be found, older workers are employed in better matches. Interestingly, old workers are also more likely to be employed in lower match productivity jobs compared to prime-age workers. Moreover, since job-finding probabilities are lower, older workers stay longer in these matches. These results are consistent with the observed employment prospects of older workers who very often are employed in either high level long tenure positions or in entry level jobs for short durations.

Summarizing the discussion above, flows in the model are driven by five channels: innovations in home production, UI benefits expiration, learning match quality, exogenous separations, and worker exit due to aging. Figure 1.3 provides a decomposition of the quantitative importance of each channel to EU, EN, and UN flows in the model. As multiple shocks might occur in a given period, we construct the decomposition by counting the flows due to each shock separately, given last periods state z, h, a, while we shut all other shocks down.[24]

On the one hand, home production shocks are the most important factor behind EN and UN transitions across all ages. The quantitative importance of benefits expiration for UN flows is limited for young and prime-age workers but they play a non-trivial role for older workers. This is consistent with the importance of UI benefits for the labor force participation of older workers explained above. On the other hand, the relative importance of factors contributing to EU are different across age groups. Exogenous separations play a major role for prime-age workers, while learning is the most important factor for the young and old ones. Compared to a model without learning, our model predicts more EU and UE flows. Given that young and old workers are pickier, this has a particularly strong impact on them. This makes the model generate high EU and UE rates of young workers, as in the data (see Figure 1.6).

4.2 Targeted Moments

The values of all calibrated parameters are summarized in Table 1.3. A few comments on the most important features of the parameterization follow. When eligible, unemployed workers receive around 15.7% of the average worker productivity as unemployment benefits. In our model, b does not include the value of home production, as in most models without an out of the labor force state, which explains its relatively low value. The very low value of the exogenous separation rate δ_0 implies that the vast majority of separations taking place in the model are endogenous outcomes of firm-worker decisions. This is in contrast to models without home production shocks, which often rely on high levels of exogenous job destruction rates to match the empirically observed separation rates.

The values of λ_u and λ_o imply that unemployed and OLF workers sample job opportunities 53% and 43% less often, respectively, compared to employed workers. This implies that search frictions are more severe for non-employed than for employed workers. To make the model consistent with the observed job-to-job transition rate, the calibration implies that employed workers sample job offers more often than non-employed workers. This is consistent with Faberman et al. (2017) who find that employed workers generate more job offers than non-employed workers in line with our calibration. As in the data, employed workers in our model have a lower job-finding rate since they are more selective than non-employed workers.

To actively search for a job, unemployed workers sacrifice more than 33% of their home production value. This non-trivial utility cost of unemployment helps the model

[24]For example, to quantify the impact of exogenous separation shocks, we compute the worker-firm matches that are terminated exogenously but with match productivity high enough to make workers and firms want to keep the match.

Parameter	Description	Value
ϕ	Share of home production for unemployed	0.6622
λ_u	Meeting intensity unemployed	0.5282
λ_o	Meeting intensity not in labor force	0.4322
δ_0	Exogenous separation rate	0.0067
k	Per-period vacancy posting costs	1.1407
p_h	Prob. of home production shock	0.9999
Δ_h	Magnitude of home production shock	1.5533
Δ_z	Dispersion of match specific productivity	9.8671
$\bar{b}$	Unemployment benefits	1.2158
b_R	Retirement benefits	0.8457
a_1	Second age knot for $\bar{h}(a)$-spline	23.4549
a_2	Third age knot for $\bar{h}(a)$-spline	62.9996
h_1	Home production at age 15	1.8171
h_2	Home production at age a_1	0.7830
h_3	Home production at age a_2	1.1818
h_4	Home production at age 64	1.0475

Table 1.3: Internally Calibrated Parameters

rationalize the observed LFPR and the strong persistence of the OLF state. Moreover, it is consistent with the empirical evidence regarding the large psychological and emotional costs experienced by unemployed individuals (Krueger and Mueller (2011) and Brand (2015)).The calibration has important implications for the home production process. Although the process features persistence, shocks are drawn often (p_h is estimated to be large). The states of employment and OLF are persistent in CPS, with a large mass of workers never leaving the state they begin in; the persistence of the random walk allows the model to capture this. At the same time, there are large flows among labor market states at monthly frequencies, with many workers changing their labor market status from month to month; the fact that home production shocks are drawn often makes the model consistent with this fact. Finally, the values of home production over the life-cycle have a U-shape, which enables the model to match the inverse U-shape profile of labor force participation found in the data (the profile is presented in the appendix figure 1.15).

The model matches all the targeted moments very closely, as can be seen in Table 1.2 and Figures 1.4 and 1.5. First, the average transition rates in the steady state of the model are very close to the average monthly transition rates of our CPS sample (Table 1.2). Comparing our results with the results of other three-state models of the labor market reveals that matching the average flows is not a trivial outcome but a rather a success of the model. For example, Garibaldi and Wasmer (2005) report that their model falls short in accounting for the magnitude of the UN and NU flows. Krusell

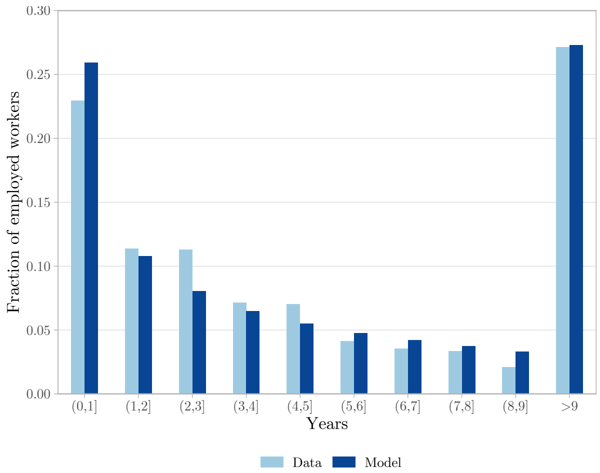


Figure 1.4: Job Tenure Distribution. Dark bars show the empirical tenure distribution in CPS, bright bars show the outcome of model simulations.

et al. (2011) also report that the UN flow is too small and the UE flow is too large in their model compared to the data.[25] On the contrary, our model can quantitatively account for all steady state flows. Furthermore, our model successfully matches the job-to-job transition rate, a flow usually not targeted in other three-state models of the labor market with the exception of Krusell et al. (2017).

With regard to the second calibration target, namely the job tenure distribution, the model-implied distribution is very close to the empirical one (Figure 1.4). The model slightly overestimates the fraction of workers with tenure less than a year and slightly underestimates the fraction of workers with tenure between two and three years. These small discrepancies are commonly found in other models in the literature using the job tenure distribution to inform match specific shocks; see Menzio and Shi (2010) for a prominent example. We should highlight that the calibration targets include only four summary groups from the tenure distribution (see Table 1.2); the good performance of the model for the ten detailed groups in Figure 1.5 serves as another source of external validation.

Various calibration features imply a persistent employment state, which helps the model produce a realistic job tenure distribution. Exogenous separations are very improbable and learning the quality of a match is completed in three months on average. Moreover, the majority of workers are employed in high-value matches. Home production is persistent as explained above, implying that the opportunity cost of employment for most workers in good matches stays low for a while. Finally, employed workers sample job opportunities often ($\lambda_e = 1$) but only workers in low value matches are interested in moving to a new job. Taken together, all these model

[25]The model of Krusell et al. (2011) can actually match the UE rate well, but this parameterization of the model implies a steady state unemployment rate of over 10%. The richer model of Krusell et al. (2017), with which our model shares many common elements, was the first model in the literature to quantitatively account for all observed labor market flows.

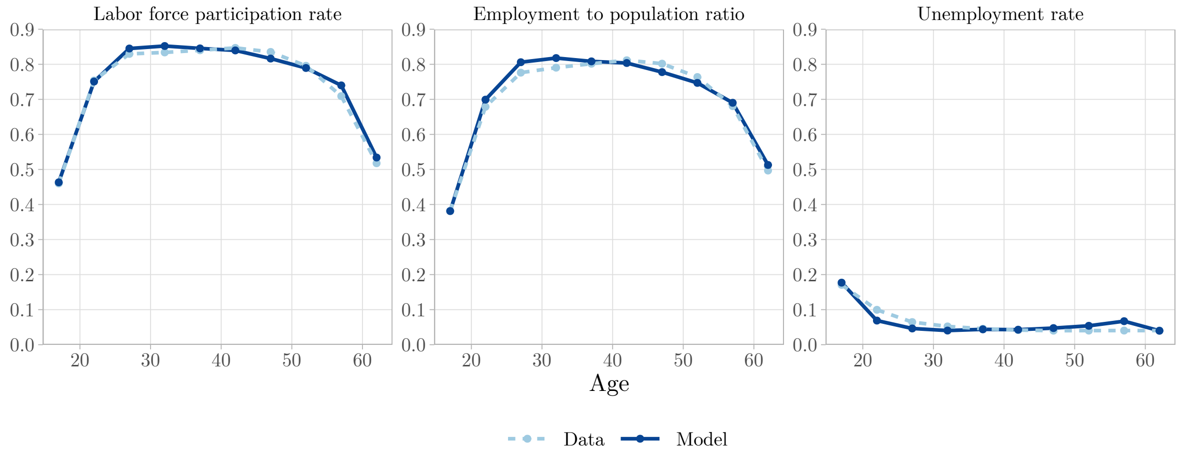


Figure 1.5: Age profile of LFPR, employment to population ratio and the unemployment rate in the model and CPS. The LFPR is a targeted moment, employment to population ratio and the unemployment rate by age is untargeted.

elements imply that a large fraction of workers stay in the same job for long tenures in the model, as in the data.

Finally, the model produces a realistic age profile for labor force participation (Figure 1.5). The successful matching of the age profile of labor force participation is reassuring for our use of age profiles of worker flows as evaluation tests of the model. It implies that the model has the potential to generate realistic transitions across labor market states over the life-cycle, while being consistent with the aggregate stocks found in the data. Again, it is important to highlight that we have not included the age profile of any flows in the calibration targets, and that the model without the life-cycle component can successfully match all monthly flows.

4.3 Untargeted Moments

The goal of this Section is to show that our model is a reliable laboratory for analyzing the effects of different unemployment insurance policies. To achieve this goal, we present the predictions of the model for a series of labor market moments which were not targeted in our calibration. The moments we chose are: i) the paths of the employment to population (E-Pop) ratio and the unemployment rate over the life-cycle; ii) the paths of all worker flows over the life-cycle; and, iii) the labor market histories of workers across four consecutive months in CPS, as analyzed by Kudlyak and Lange (2018) and Hall and Kudlyak (2019).

Our choices of untargeted moments are guided by the fact that we want to use the model to study changes in the provision of UI benefits. First, looking at the E-Pop ratio and the unemployment rate is natural, since we want to make sure that the model is consistent with all important labor market stocks. The impact of UI on labor

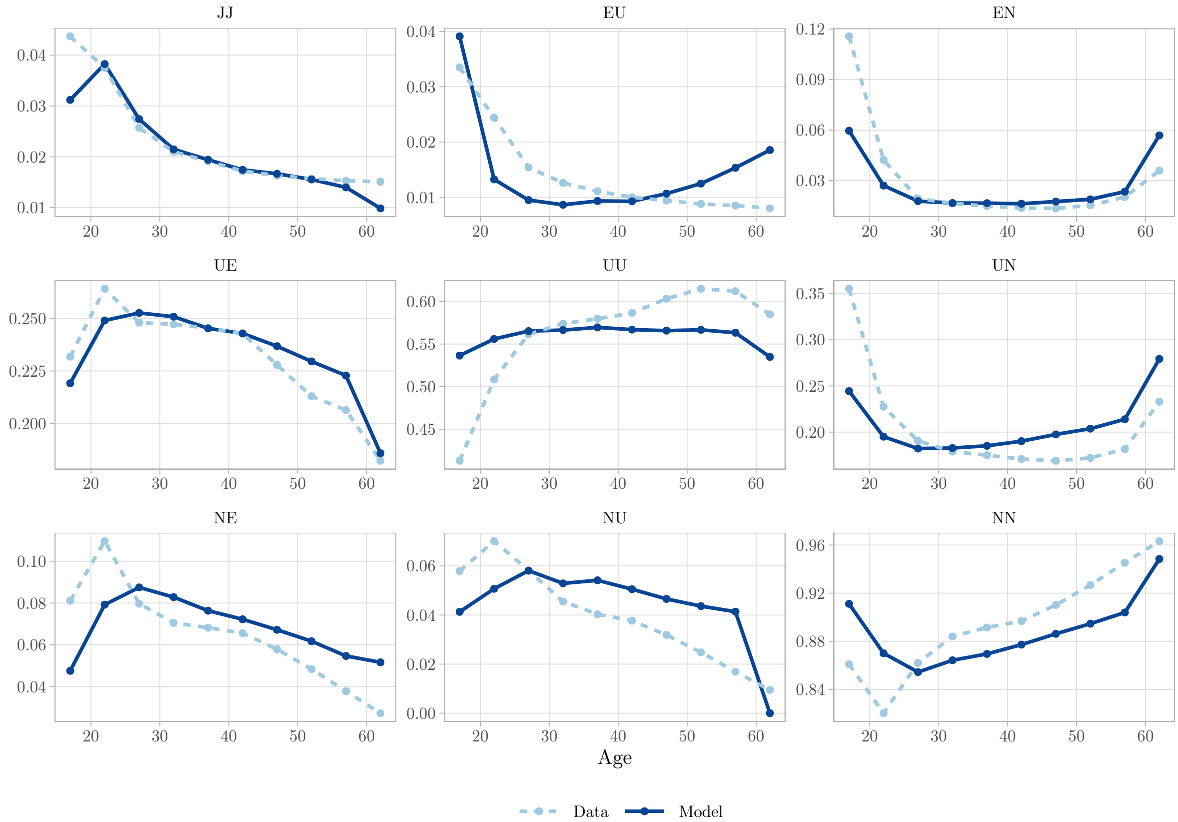


Figure 1.6: Age profile of flows in CPS compared to model simulations. The life-cycle profile of flows is untargeted.

market stocks is an important part of the policy debate, hence it is crucial for the calibrated model to replicate those. Second, we look at labor market flows over the life-cycle and the four-month labor histories because they are measures of workers' labor market attachment. Workers with strong labor market attachment may respond differently to UI changes compared to workers with weak attachment. For example, Lalive (2008) and Tatsiramos (2010) show that in countries in which UI can be used as a bridge to early retirement, unemployment for older workers is an absorbing state. Similarly, Kudlyak and Lange (2018) and Hall and Kudlyak (2019) find that a worker's labor market history preceding a given month is a strong predictor of the conditional probability of a move from non-employment to employment in that month. Hence, for the model to give reliable predictions to UI counterfactuals, it should capture these aspects of worker heterogeneity. This is particularly important for the exercise we perform in Section 5.3, where we study whether UI reforms have differential effects across the age distribution.

The untargeted moments generated by the model are close to the empirical ones, showing that the model is a reliable laboratory for the study of UI policies. First, as shown in Figure 1.5, the model-implied E-Pop ratio and unemployment rate follow closely their empirical counterparts over the life-cycle. The model slightly overesti-

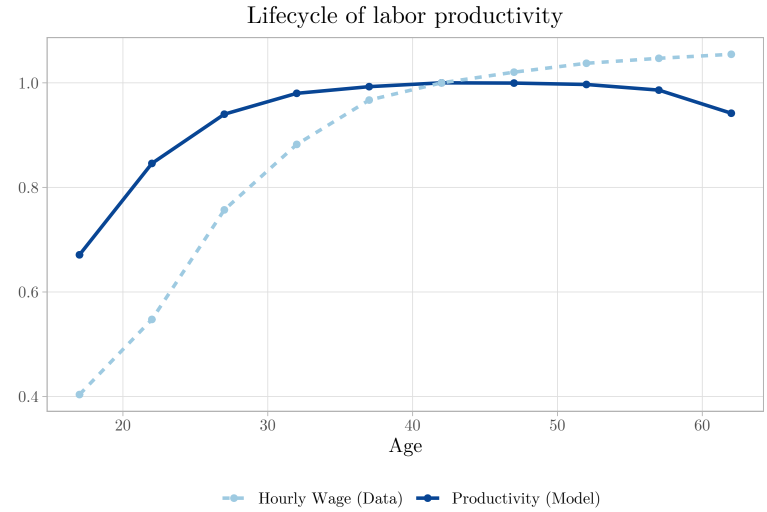


Figure 1.7: Average labor productivity in the model and hourly wages from the March CPS supplement. All values are normalized by the 6th age group (40-44). CPS hourly wages are conditional on at least 8 hours of work per week.

mates (underestimates) the unemployment rate for older (younger) workers. These small differences between the model and the data can be attributed to forces we do not explicitly model. Older individuals, for example, may have accumulated assets which ease their transition out of the labor force just before retirement, while they still actively look for jobs in the model.

Second, the model-implied paths of worker flows over the life-cycle are very close to the empirical ones (Figure 1.6). For many flows, such as the JJ, UE, and NE flows, the paths are almost identical to the data. This is particularly important because some of these flows have not been studied by the UI literature, while our structural framework seems appropriate to do so. For most other flows, such as UN and EN, the model delivers the right shape and levels similar to the data. Given that the only targeted life-cycle moment is the LFPR, this result is a non-trivial success of the model, showing that it can predict realistic worker movements across multiple untargeted dimensions. As explained earlier, the age dimension is especially important because it provides information about how older workers may be differently affected by UI policies compared to prime-age or younger workers.

As an additional external validity check, we compare the life-cycle path of labor productivity implied by the model with hourly wages by age in the data. We chose labor productivity as the relevant model object, because of the well-known fact that wages are indeterminate in directed search models (Menzio and Shi, 2011). Since labor productivity by age is not readily available in the data, we use hourly wages as a proxy. The evolution of productivity in the model mimics the life-cycle evolution of wages. Both in the model and in the data, there is a steep increase until age 40,

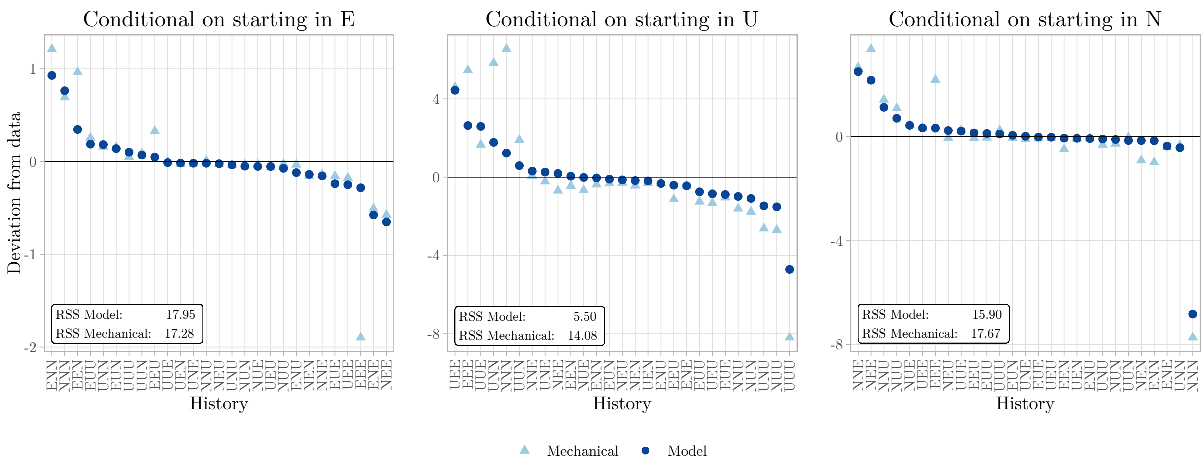


Figure 1.8: Difference between simulated and observed frequencies of four-months labor market histories in CPS. Mechanical frequencies are constructed by multiplying the monthly transition probabilities from CPS. The histories are sorted by the model deviations. RSS denotes the sum of squared percentage deviations.

after which labor productivity and wages flatten out. This pattern is generated in our model by workers moving to better matches over the life-cycle. During prime age, workers' labor force attachment stabilizes, which implies that workers can hold on to their good matches, which generates the flattening of labor productivity.

Third, the labor histories of workers in the model are broadly consistent with the four-month histories reported in CPS (Figure 1.8). There are two relevant comparisons shown in Figure 1.8: the first is between the model-implied fractions of various four-month worker histories and the fraction of these histories in the data. As can be seen in Figure 1.8, for most four-month histories the deviations of model predictions from the data are almost zero. However, there are few histories that the model is not able to capture.

To get a better sense of the model's fit, we implement the second comparison shown in Figure 1.8: we compare the model's performance with the worker histories implied by the mechanical projection of the CPS monthly transition rates. This comparison can tell us how much more information about workers' prospects the model carries over the information contained in the aggregate month-to-month transition rates. The answer is "a non-trivial amount" for workers starting out of the labor force, and "quite a lot" for workers starting in unemployment (the two models are very close for workers starting in employment). The fact that the model considerably improves upon the prediction of the mechanical approach for unemployed workers is especially useful for our analysis of UI benefit reforms. The directed search protocol helps the model generate this improvement. Workers in the same labor market state but with different outside options face different probabilities to leave this state, which helps the model account for various histories. For example, some OLF workers have much higher home production than others; the former will be the ones mostly staying in this state over time (performing histories such as NNNN), while the latter will be transitioning across labor market states (performing histories such as NENU).

It is important to understand why the four-month histories are of particular importance for our study. Following workers over time provides a panel dimension, which is lost when one considers only monthly transition rates. As Kudlyak and Lange (2018) and Hall and Kudlyak (2019) emphasize, this panel dimension provides important information about the underlying worker heterogeneity, which may be important for the analysis of UI benefits. In intuitive terms, the observed monthly worker flows are the result of some workers changing labor market state often and some workers changing status rarely. The four-month histories shed light to how many workers of each type are present in the workforce. Importantly, this information is also indicative of a worker's labor market attachment; to see this, compare a worker with EEEE versus NNNN history. It is well-known that workers with different degrees of attachment behave very differently in the labor market.[26] As shown in Figure 1.8, our model captures a substantial amount of this panel dimension, implying that it is consistent with the underlying worker heterogeneity that may be important for the effects of UI policies.

5 Policy Exercises

We next use the model as a laboratory to study the effects of an increase in UI benefits on the labor market. These effects have been controversially discussed by the general public as well as the academic literature. Using our equilibrium model, we evaluate the effects of two different changes in the UI system. We study an extension of UI benefits from 26 weeks to 99 weeks, as well as an equally expensive 17.6% increase in UI benefits, while keeping the duration at 26 weeks. Our main analysis focuses on a comparison between steady states but we also present the transition paths in appendix C. The next subsection presents the aggregate results of these two policy reforms. Next, we decompose the main driving forces behind the aggregate effects. Finally, the last subsection studies the heterogeneous effects by worker age.

5.1 Aggregate Effects of UI Reforms

Table 1.4 shows the effects of the two reforms on employment, labor force participation, unemployment rate, GDP, and labor productivity.[27] Both reforms lead to modest

[26] As an example along these lines, Mankart and Oikonomou (2017) show that second earners change their labor market behavior more often than primary earners over the business cycle.

[27] Notice that in all figures we compute percentage changes before rounding the numbers.

	Baseline	UI +17.6%		99 weeks UI	
Moment	Value	Value	Pct. Change	Value	Pct. Change
E-Pop	0.704	0.699	-0.732%	0.699	-0.776%
LFPR	0.748	0.746	-0.175%	0.747	-0.018%
U-Rate	0.058	0.063	9.090%	0.065	12.356%
GDP	5.466	5.422	-0.801%	5.420	-0.840%
Labor Prod.	7.759	7.754	-0.069%	7.754	-0.065%

Table 1.4: Effects of more generous UI benefits. The table reports how labor market stocks, GDP and labor productivity respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

decline in the E-Pop ratio of 0.7%. This, together with a slight reduction in productivity leads to a 0.8% decline in output across both scenarios. The main difference between the two policies lies in the response of the unemployment rate, which rises by 12% for the UI benefits duration extension, and by 9% for the increase in UI benefits. The stronger increase in the unemployment rate is not due to fewer jobs, but because more workers stay in the labor force with the UI extension to 99 weeks. While it is sometimes argued that more generous UI benefits would lead to an increase in the LFPR as more workers are incentivized to search, we find that in both scenarios the LFPR rate is largely unchanged. We also conducted a number of sensitivity checks of our results with respect to the parameters we set externally. Table 1.12 in the appendix shows that these results are robust to different parameterizations.[28] Moreover, in appendix D we show that our main conclusions are robust to imposing a tax on match output to finance UI benefits. The reason behind this is that expenditures on UI benefits constitute only 0.4 percent of GDP, thus the distortionary effects of tax changes due to UI benefit reforms are quantitatively not important.

In order to understand how these changes come about, we study the responses of the underlying labor market flows. These responses are driven by two forces: (1) behavioral changes by firms and workers through changes in their policy functions, which are reported in Figure 1.9, and (2) compositional changes in the pools of employed, unemployed, and out of the labor force workers across different age and home production levels. Table 1.5 presents the overall percentage changes of labor market flows. In addition, it reports the behavioral changes only, which are the changes induced solely by policy function changes, while holding the distribution of agents across the states space (z, h, a) fixed to the pre-reform level. The behavioral change

[28]We use both higher and lower levels of the learning speed α, as well as the elasticity of the matching function γ. In addition, instead of using UI expenditures over GDP as the target for UI benefits, we use UI expenditures over labor income in the data. This essentially implies higher UI benefits, and we show that our findings are robust with respect to this change.

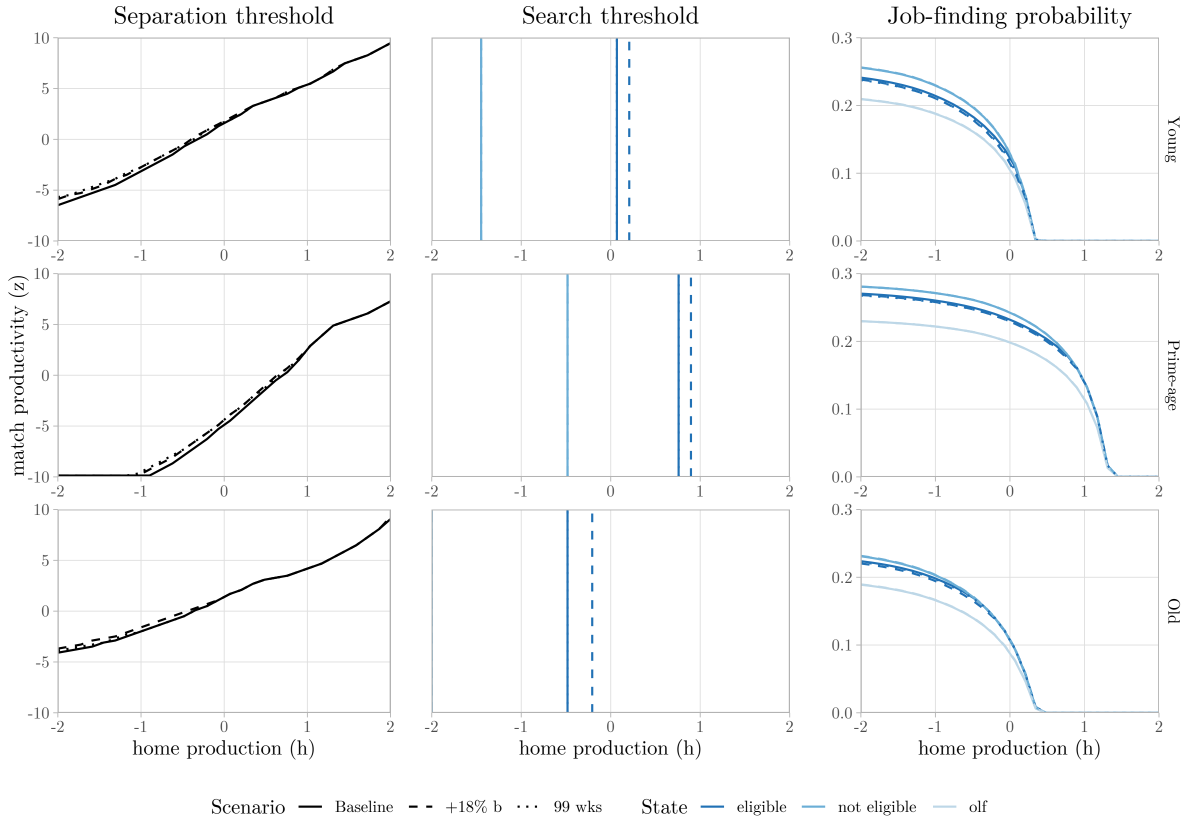


Figure 1.9: Policy functions and job-finding probability under different UI policies by age groups.

can be also thought of as the change on impact along the transition path (see appendix C). On impact, the distribution has not change yet. Over time, the distribution converges to the new steady state, and so do the flows, which then are a combination of behavioral and compositional changes.

Overall, both reforms have very similar effects on policy functions. More generous UI leads to a higher reservation productivity for viable matches (left column of Figure 1.9), and lower job-finding probabilities (right column) across all age groups.[29] This can also be seen in the flow results of Table 1.5. Focusing on behavioral changes, for which the distribution of agents over (z, h, a) is fixed, both reforms have a similar impact on flows, with the exception of the UN rate, which declines much more with the 99 weeks UI extension.

The UI reforms affect the UN flow through two forces. First, large enough positive shocks to home production lead unemployed workers to drop out of the labor force. Because of the change in the search threshold, active search now covers a larger range of h values. Thus, the probability of receiving a high enough shock to leave the labor force declines, which reduces the UN flow. Second, some workers only search while receiving unemployment benefits. In the case of extended UI benefits, the probability

[29] Figure 1.10 in the appendix shows the policy function for all ages.

	Baseline	UI +17.6%			99 weeks UI		
	Value	Value	Overall Change	Behavioral Change	Value	Overall Change	Behavioral Change
JJ	0.021	0.020	-2.316%	-2.494%	0.020	-2.508%	-2.714%
EU	0.013	0.015	14.370%	15.606%	0.014	9.914%	11.500%
EN	0.024	0.023	-2.765%	3.175%	0.024	-0.138%	5.576%
UE	0.234	0.229	-2.047%	-0.371%	0.228	-2.714%	-0.629%
UN	0.208	0.206	-1.308%	-5.354%	0.179	-14.324%	-11.423%
NE	0.063	0.062	-0.661%	0.298%	0.062	-1.719%	0.210%
NU	0.038	0.038	0.592%	3.189%	0.037	-2.428%	3.188%

Table 1.5: Effects of more generous UI benefits on labor market flows. The table reports how flows respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

of an UI expiration declines, which leads to a significant reduction (-14%) in the UN rate. This decline in the UN rate changes the composition of unemployed and OLF states. Workers transitioning from U to N have a higher home production h compared to unemployed workers and a lower h compared to OLF workers. Thus, the declining UN rate leads to an unemployment and out of the labor force pool with higher home production.

These compositional changes affect the flows into the labor force, NE and NU. In principle, more generous UI benefits incentivize workers to rejoin the labor force, which can be seen in the positive workers' behavioral response for both NE and NU. However, this is counteracted by the above described compositional effect, which pushes to the opposite direction than the behavioral change. Because high h workers have a lower propensity to enter the labor force, the overall higher home production level in the pool of out of the labor force workers leads to a decline in the NE rate. The compositional effect is stronger for the UI 99 weeks extension, as the extension has a larger effect on the UN flows than the increase in UI benefits. Finally, the NU rate even declines for the UI extension, and remains close to unchanged for the benefit increase.

Next, we move to the UE, EU, and EN rates. The post-reform job-finding rate declines because of two reasons. First, the unemployment pool after the reforms consists of workers with higher home production and, as a result, lower job-finding probabilities; this puts a downward pressure on UE flows. Second, the UE rate declines because firms have to offer higher value jobs in response to higher UI benefits, which depresses vacancy creation. The separation rates increase under both UI reforms. The higher reservation threshold for match specific productivity leads to fewer viable matches, and thus to more separations and higher EU flows. Abstracting from compositional changes, the same force would lead to an increase in EN transitions. But because UI reforms affect older workers more (as we show in Section 5.3), the pool of employed workers shifts towards prime age workers with a stronger labor force attachment. This compositional change undoes the behavioral effect, and the EN rate declines after both reforms.

In addition, the overall higher separation rates lower the return of opening new vacancies , as fewer of these jobs survive the revelation of the match specific productivity. This depresses the job-finding rates for unemployed and employed workers even further, which can be seen by the decrease in both UE and JJ rates. The lower job-to-job transition rate also explains the decrease in labor productivity. Even though the reservation productivity is now higher, fewer workers climb up the match specific productivity ladder. These two effects roughly cancel each other out, leaving the overall labor productivity almost unchanged. This is in contrast to models without job-to-job transitions, where the higher reservation productivity unambiguously leads to higher labor productivity (Acemoglu and Shimer, 1999). This result would be missed by a framework without an explicit role for job-to-job transitions.

5.2 The Contribution of Different Model Channels

One of the key contributions of this paper is to study the effects of UI reforms while explicitly taking into account the response of the labor force participation margin, which is typically abstracted from in the literature (Nakajima, 2012; Hagedorn et al., 2013; Mitman and Rabinovich, 2015). Importantly, our model also incorporates endogenous vacancy creation and job-to-job transitions. In this Section, we evaluate the quantitative contributions of these mechanisms for the economy's response to UI reforms.

The aggregate UI reform effects in the model originate from several distinct margins of adjustment. First, the separation margin, i.e. the reservation productivity for viable matches, changes. Second, we define the participation margin as the adjustment in the home productivity threshold for participating in the labor market. In the case of the 99 weeks UI benefit extension, there is an additional effect in the participation margin: because the probability of UI expiration declines, fewer workers lose UI eligibility, which in turn affects labor market stocks and flows. Third, we define the matching margin as the sum of adjustments due to changes in vacancy creation and changes in the submarket search decisions of employed and non-employed workers. We use our model to disentangle the contribution of each one of these channels to the aggregate effects of UI reforms. To do so, we compute the total effects of changing each margin from pre- to post-reform one by one, while holding all other margins fixed at their pre-reform levels.

	UI +17.6%				
Values	E-Pop	LFPR	U-Rate	GDP	GDP/L
Separation margin	-0.77%	-0.50%	4.46%	-0.84%	-0.07%
Participation margin	0.03%	0.30%	4.28%	0.03%	-0.00%
Matching margin	0.01%	0.02%	0.20%	0.01%	0.00%
Total effect	-0.73%	-0.18%	9.09%	-0.80%	-0.07%
	99 weeks UI				
Values	E-Pop	LFPR	U-Rate	GDP	GDP/L
Separation margin	-0.78%	-0.49%	4.71%	-0.85%	-0.07%
Participation margin	0.02%	0.45%	6.88%	0.02%	-0.00%
Matching margin	0.00%	0.01%	0.20%	0.00%	0.00%
Total effect	-0.78%	-0.02%	12.36%	-0.84%	-0.06%

Table 1.6: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

Table 1.6 reports the contribution of each individual channel on aggregate stocks, while Table 1.7 reports the decomposition results for labor market flows. In all cases, the individual effects sum up approximately to the total effect, indicating that interaction effects between the channels play a limited role. For both reforms, the change in the separation threshold has the largest single impact on employment, LFPR and GDP, while the participation margin plays an important role for the reaction of the unemployment rate and LFPR. The matching margin plays a modest role. This is due to the fact that the job finding rates decline by a large part because of compositional changes in the unemployment pool, as can be seen in Table 1.5. These compositional changes in turn are driven by the participation margin, as can be seen in Table 1.7. The finding that the separation margin is quantitatively important for the effects of UI reforms is in line with recent evidence in Hartung et al. (2020), which shows that lower separation rates into unemployment accounted for 76% of declining unemployment after the Hartz reforms (which cut eligibility duration in Germany).

Based on the limited importance of the matching margin for labor market stocks, one may conclude that modeling job-to-job transitions is not necessary for a comprehensive understanding of UI reforms. This conclusion, however, would be premature. The separation margin has a profound effect on the job-to-job transition rate, which in turn affects labor productivity. Due to the higher reservation threshold, many low productivity jobs are not viable anymore after the revelation of the match-specific productivity. As in standard search models without job-to-job transitions, this force pushes labor productivity up, as the remaining jobs are of higher productivity (Ace-

	UI +17.6%						
Values	JJ	EU	EN	UE	UN	NE	NU
Separation margin	-2.37%	6.99%	1.13%	-0.11%	-0.70%	0.03%	-0.32%
Participation margin	-0.01%	7.20%	-3.87%	-1.53%	-0.44%	-0.95%	1.00%
Matching margin	0.07%	0.06%	0.04%	-0.40%	-0.06%	0.27%	-0.06%
Total effect	-2.32%	14.37%	-2.77%	-2.05%	-1.31%	-0.66%	0.59%
	99 weeks UI						
Values	JJ	EU	EN	UE	UN	NE	NU
Separation margin	-2.54%	7.09%	1.28%	-0.02%	-1.18%	0.01%	-0.26%
Participation margin	-0.02%	2.76%	-1.43%	-2.12%	-12.70%	-1.85%	-1.87%
Matching margin	0.06%	0.05%	0.03%	-0.36%	-0.11%	0.19%	-0.06%
Total effect	-2.51%	9.91%	-0.14%	-2.71%	-14.32%	-1.72%	-2.43%

Table 1.7: Contribution of individual channels to the aggregate UI reform effects. The table shows the effect of moving individual policy functions from pre to post-reform level, while holding all other policy functions fixed at pre-reform level.

moglu and Shimer, 1999). But in our model with job-to-job transitions, there is a counteracting force. Workers in low productivity matches have a high job-to-job transition probability (see Figure 1.2), and therefore many would have transitioned to high productivity matches. But because of the higher reservation productivity, these jobs are being destroyed before workers get the chance to move to higher productivity matches through job-to-job transitions. This explains the overall decline in job-to-job transitions, as well as the slight decline in labor productivity.

Last but not least, the changing participation margin is quantitatively important for the aggregate effects of UI reforms. First, the participation margin counteracts the drop in LFPR due to the separation margin. Second, and perhaps more importantly, it alone accounts for 50 percent of the unemployment rate responses. Thus, a model without endogenous participation would miss a substantial part of the unemployment response due to UI changes. This highlights the importance of taking the labor force participation decision explicitly into account when considering changes to the UI system.

5.3 The Age Effects of UI Reforms

One of the contributions of the paper is to incorporate the life-cycle dimension in a directed search model with endogenous participation. As we argued in Section 4.3 the model matches the life-cycle patterns of labor market flows very well. In this Section we show that different age groups respond differently to UI reforms, implying that

		Baseline	UI +17.6%		99 weeks UI	
	All	0.704	0.699	−0.732%	0.699	−0.776%
LFPR	Young	0.607	0.610	0.461%	0.611	0.683%
	Prime-age	0.831	0.831	−0.075%	0.831	0.013%
	Old	0.637	0.629	−1.176%	0.632	−0.809%
	All	0.748	0.746	−0.175%	0.747	−0.018%
U-Rate	Young	0.110	0.118	7.476%	0.121	10.098%
	Prime-age	0.046	0.049	8.249%	0.051	11.035%
	Old	0.056	0.064	14.335%	0.067	20.242%
	All	0.058	0.063	9.090%	0.065	12.356%
Labor Prod.	Young	6.399	6.411	0.183%	6.412	0.209%
	Prime-age	8.034	8.038	0.042%	8.039	0.053%
	Old	7.893	7.839	−0.685%	7.835	−0.731%
	All	7.759	7.754	−0.069%	7.754	−0.065%

Table 1.8: Effects of more generous UI benefits on different age groups. The table reports how labor market stocks and labor productivity for young, prime-age and old workers respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

modeling the age-dimension is important for a comprehensive understanding of the effects of more generous UI benefits.

Table 1.8 reports the effects of more generous UI benefits, disaggregated by young (15-24), prime-age (25-54), and old workers (55-64), whereas the effects on the flows is relegated to the appendix in Table 1.10. There are two interesting implications of this analysis. First, the prime-age group responds less to UI changes than the other two groups. The only exceptions are E-Pop and the unemployment rate, for which the response of prime-age workers is similar to the response of young workers. The small change in the behavior of prime-age workers is a result of their stronger attachment to the labor market. Prime-age workers are not affected much by UI generosity in the model, due to their relatively low home production and the ample time they have to reap the benefits of job-to-job transitions. Second, another interesting result of Table 1.8 is the large magnitude of changes found among old workers. As shown in Figure 1.2, a non-trivial mass of old workers are in good matches but they are also close to being indifferent between employment and non-employment, due to their high home production. The increase in UI benefits induces these workers to leave employment, and increases the probability of dropping out of the labor force when benefits expire. At the same time, the job finding rate of older workers features the largest drop among all age groups, as can be seen in Table 1.10. Importantly, this result that older workers are more responsive to changes in UI benefits is in line with the evidence provided by Michelacci and Ruffo (2015) based on SIPP and CPS data for the US.

The final take away from this table is that the large changes exhibited by the old workers have a small impact on the aggregate responses of UI increases. There are two reasons for this, of which the first is mechanical: old workers form a group of relatively small size. The aggregate results are affected much more by the modest responses of prime-age workers, because they are numerous. The second and perhaps more interesting reason is that the response of old workers is counteracted by a response of some other group that has the opposite sign. For example, the LFPR of young workers increases with UI improvements, which counteracts the large decrease found among old workers. Summarizing, changes in UI generosity affect different age groups in heterogeneous ways. Therefore, states with older populations will respond differently to UI reforms than younger states. Thus, policy makers and researchers should take into account the age structure of the economy for a comprehensive evaluation of UI reforms.

6 Conclusion

The goal of this paper is to analyze the positive effects of unemployment insurance (UI) reforms on labor market flows and stocks. To do so, we develop an equilibrium life-cycle search model featuring *all* labor market flows, as well as endogenous job creation by firms. Importantly, compared to the previous literature, our model includes job-to-job transitions and a labor force participation decision, both of which play an important role for the analysis of UI reforms. The first source of heterogeneity in the model is home production, which changes over time due to workers' aging and idiosyncratic shocks. Workers with high levels of home production tend to stay out of the labor force, while workers with low levels of home production engage in active jobs search as unemployed. On the other side of the market, firms create jobs with different characteristics directed to workers with different outside options. The second source of heterogeneity in the model is match-specific productivity: job-worker matches differ with respect to the output produced. Moreover, matches start out with unknown productivity, which is learned over time. The opportunity of finding a better match incentivizes employed workers to look for jobs and transition to more productive matches over time.

We calibrate the model to a set of empirical moments from CPS. Our calibration targets include the aggregate labor market flows, the job tenure distribution, as well as the profile of labor force participation over the life-cycle. To gauge the empirical validity of the model, we compare its performance with two sets of untargeted empirical moments, also from CPS: the labor market flows over the life-cycle, and the four-month labor market histories of workers. The model successfully replicates all targeted moments and predicts very realistic profiles for most life-cycle flows and worker labor market histories, showing it is reliable laboratory to study the positive effects of UI reforms.

The central contribution of the paper is to use the model to study the effects of two UI benefits reforms: an extension of UI benefits to 99 weeks, as well as an equally expensive 17.6% benefits increase, while the eligibility duration is held constant. The model predicts that the 99 weeks extension leads to a slight decrease in the employment to population ratio but to a significant increase in the unemployment rate; the labor force participation rate and labor productivity stay roughly the same after the reform. The equally expensive increase in benefits yields a smaller increase in the unemployment rate and a larger decrease in the labor force participation rate. Both reforms have similar effects on GDP, labor productivity, and job-to-job transitions. Importantly, we show that disregarding the effect of job-to-job transitions and flows in and out of the labor force would significantly bias the response of labor productivity and the unemployment rate to UI reforms, respectively.

To be more specific, our exercise yields three important policy-relevant messages. First, based on the results of previous studies, commentators have argued that more generous UI benefits would reduce workers' exit from the labor force. We show that despite this being true in our model, taking into account the response of all flows, the LFPR modestly declines. Second, as Acemoglu and Shimer (1999) point out, more generous UI makes workers pickier and may increase labor productivity. In our model, this result does not hold because of a counteracting force: more generous UI reduces job-to-job transitions, which leads fewer workers climbing up the job ladder to more productive jobs, ultimately leaving labor productivity unchanged. Third, the responses of different age groups to UI policy changes are heterogeneous, with older worker exhibiting larger responses than prime-age and young workers. To conclude, we argue that any successful positive analysis of UI reforms should take the response of job-to-job transitions, the participation decision of workers, as well as age differences into account.

Appendices

A Computational Appendix

We solve for the equilibrium of the model using the following procedure:

First, we discretize the continuous distribution for productivity as well as the continuous process for home production. For the idiosyncratic productivity, z, we use 100 equally spaced grid points between $-\Delta_z$ and Δ_z. Furthermore, we define an additional 101st state which denotes the case that the match-specific productivity is still unknown. We approximate the continuous process for idiosyncratic home production, h, by defining 30 points on an equally spaced grid between -2 and 2 and using the Tauchen method to assign transition probabilities between these grid points. As discussed in the main text, these bounds are necessary as we model a random walk which is unbounded. Additionally, we evaluate the spline for home production by age, $\bar{h}(a)$, for 10 age groups. Along this dimension, agents can transition at most one step each period with probability 0.0167. Lastly, we keep track of the eligibility status b for unemployed agents. In total, there are $30 \times 10 \times (101 + 2 + 1) = 31,200$ states.

Second, we solve for the policy functions given the free entry condition using value function iteration. This algorithm can be executed with low computational cost as the optimal submarket and the associated job-finding probability can be solved in closed-form. Additionally, we use the independence of the various shocks to simplify the computation of the expected value next period.

Third, given the optimal decision of the agents and the job-finding probabilities, we compute the steady state. Note that we assume that agents entering the model draw their first state from the stationary distribution. Since the transition matrix is relatively large (31,200 $\times$ 31,200), this step is computational expensive. We alleviate this problem by exploiting the sparsity of the matrix and solve for the eigenvector associated to the largest eigenvalue. Since we need to repeat this procedure many times, we employ an iterative solver for finding the eigenvector and solve the model in C++.

To calibrate the model, we use the method of simulated moments and minimize the relative distance between the data target and the model moment. This makes the moment conditions unit free and, hence, we use an identity weighting matrix. The problem can then be described as finding the global minimum of a 15-dimensional function with an unknown functional form. As this problem is notoriously hard to solve, we use the Matlab global optimization solver "particle swarm" with 200 particles and restart this algorithm over 800 times with random initial particles. Finally, we choose the best model among all these repetitions.

B Policy Functions for all Age Groups

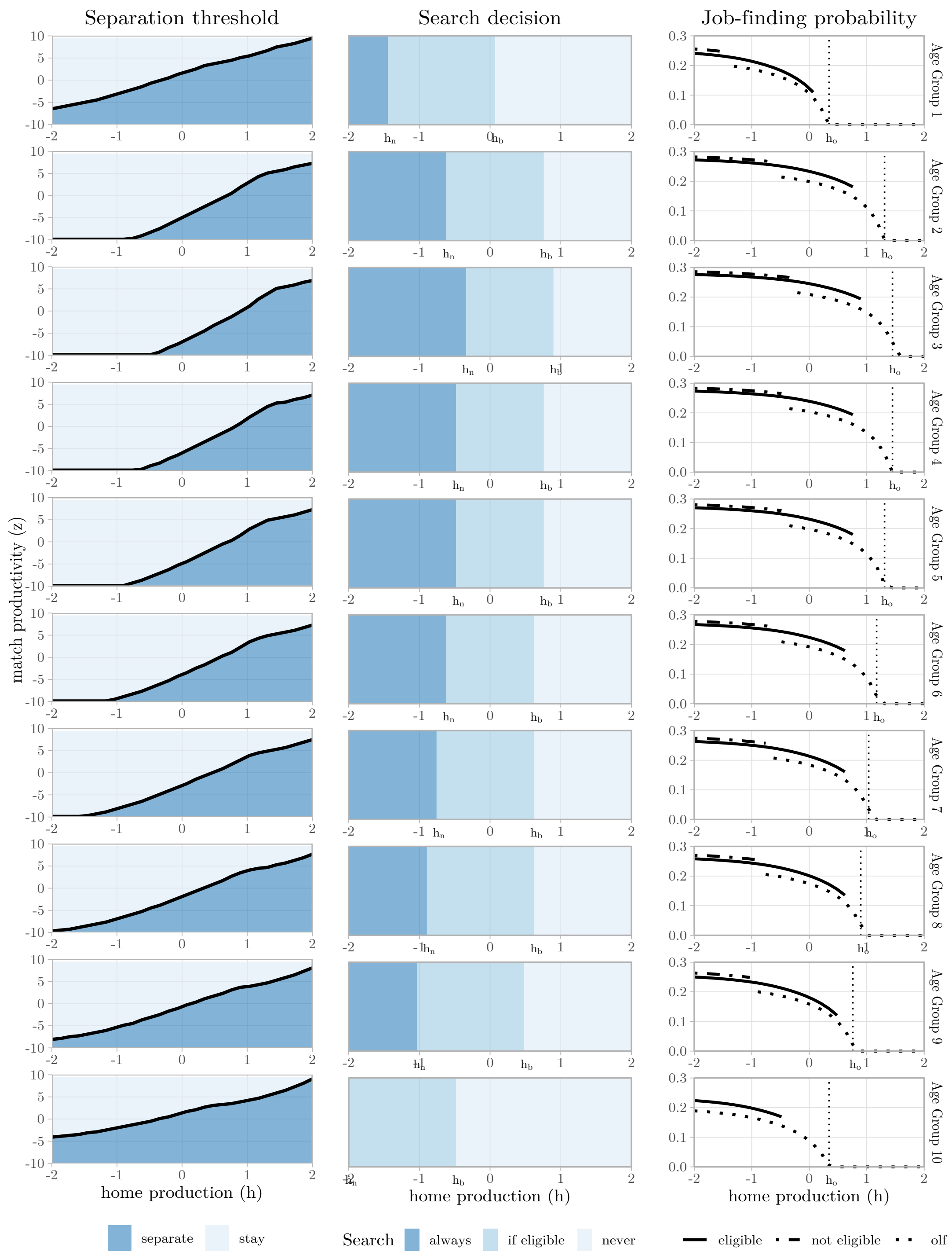


Figure 1.10: Policy functions for all age groups.

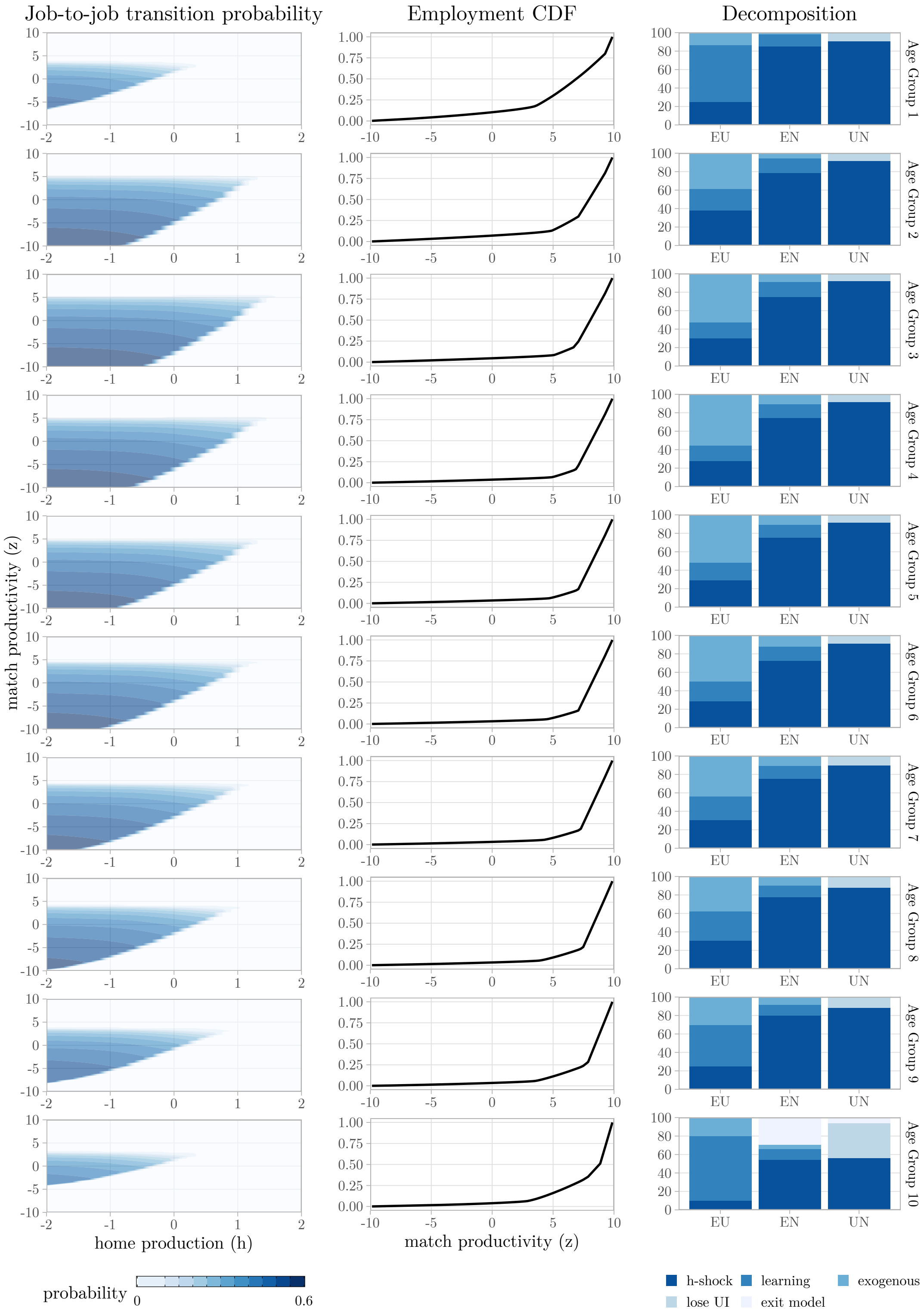


Figure 1.11: Job-to-job transition probabilities, employment CDF, and decomposition for all age groups.

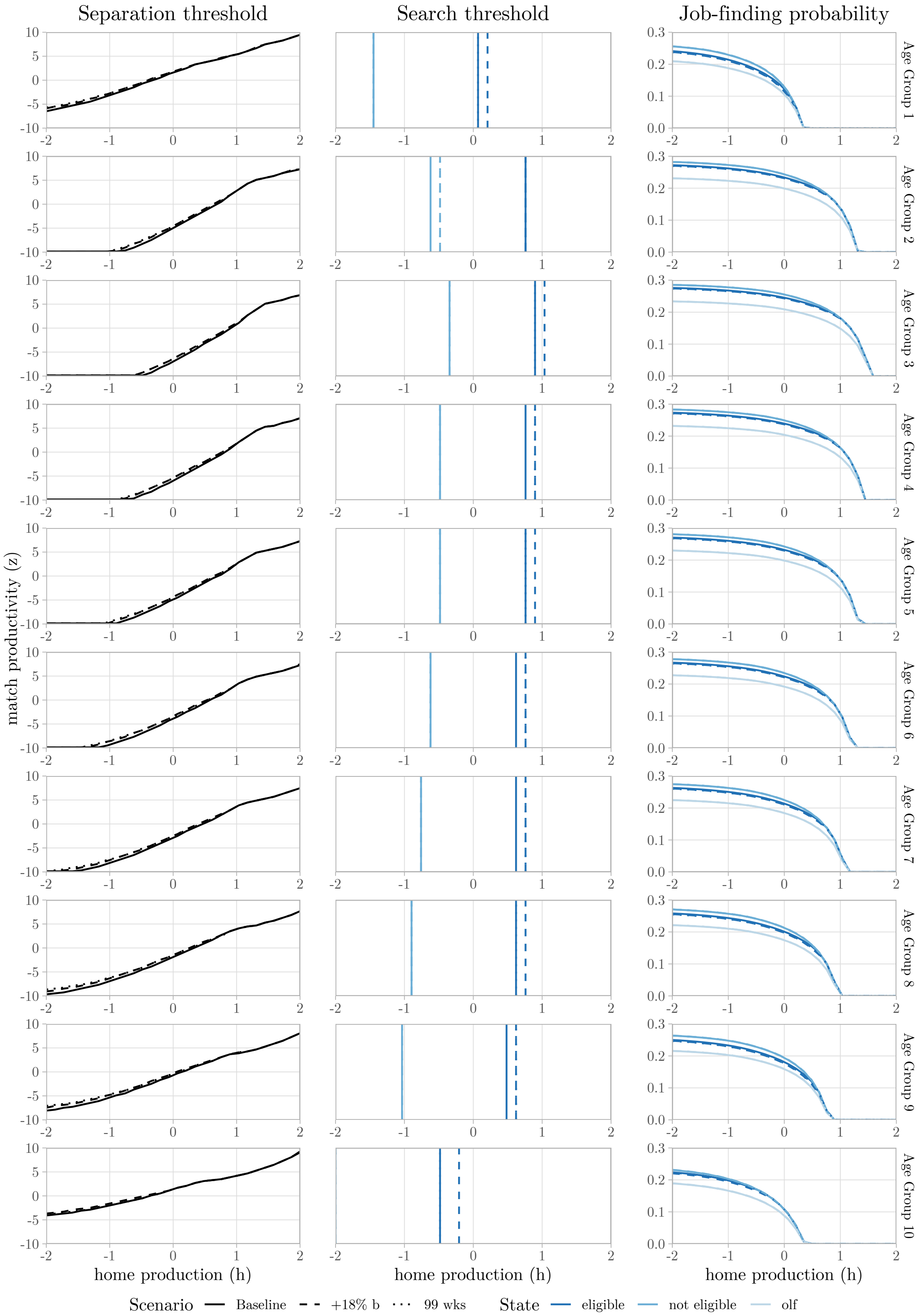


Figure 1.12: Policy functions across the scenarios for all age groups.

C Transition Paths

Figures 1.13 and 1.14 present the transition paths for labor market flows and stocks following the two UI reforms described in the main text. The shock is an unexpected permanent change of UI generosity which occurs at period 0 (when the economy is at the steady state with the previous level of unemployment benefits). We plot the transition paths from the old to the new steady state.

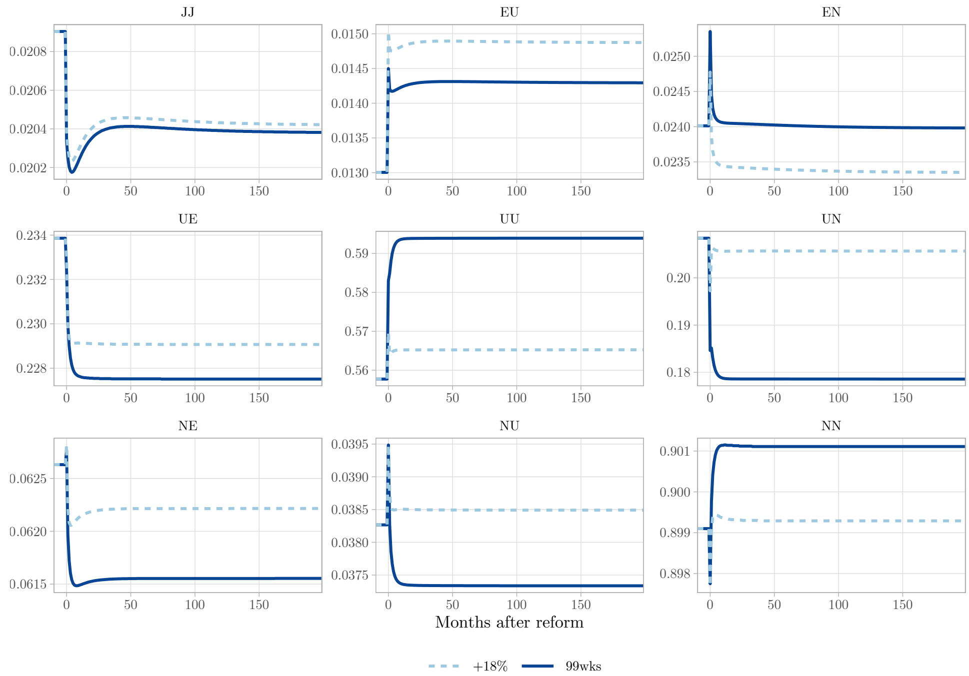


Figure 1.13: Transition paths of flows for a permanent change in the UI system.

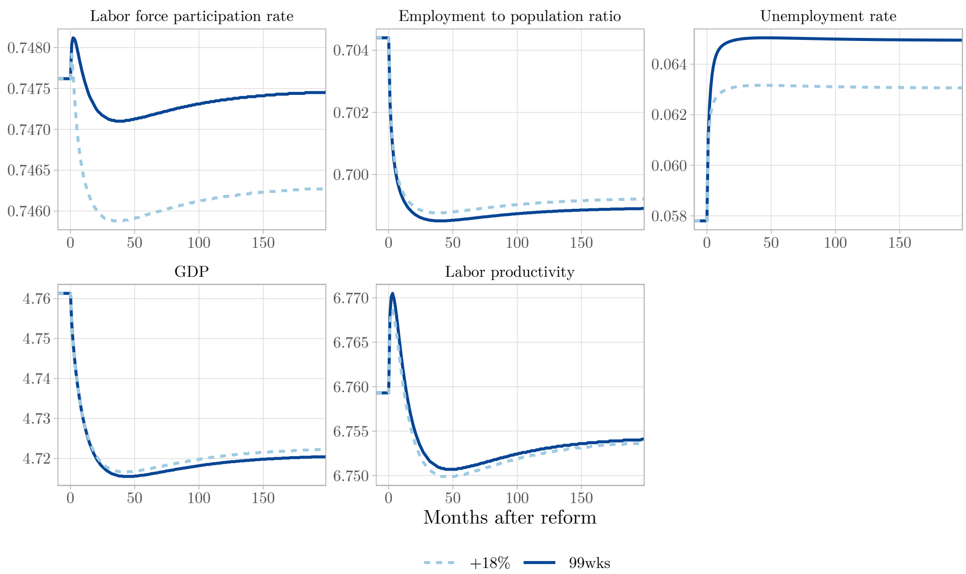


Figure 1.14: Transition paths of stocks for a permanent change in the UI system.

		Baseline	UI +17.6%		99 weeks UI	
Moment	Tax	Value	Value	Pct. Change	Value	Pct. Change
E-Pop	No	0.704	0.699	-0.732%	0.699	-0.776%
	Yes	0.698	0.695	-0.425%	0.695	-0.481%
LFPR	No	0.748	0.746	-0.175%	0.747	-0.018%
	Yes	0.742	0.743	0.088%	0.744	0.254%
U-Rate	No	0.058	0.063	9.090%	0.065	12.356%
	Yes	0.060	0.064	8.101%	0.066	11.570%
GDP	No	5.466	5.422	-0.801%	5.420	-0.840%
	Yes	5.382	5.357	-0.468%	5.354	-0.518%
Labor Prod.	No	7.759	7.754	-0.069%	7.754	-0.065%
	Yes	7.711	7.707	-0.043%	7.708	-0.037%

Table 1.9: Effects of more generous UI benefits. The table reports how labor market stocks, GPD and labor productivity respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed.

D Fully-Financed UI System

In the main body of the paper, we make the simplifying assumption that UI benefits are not explicitly financed by the government. Without this assumption, we would need to solve an additional fixed point problem for finding the tax rate that balances the government budget, rendering our calibration strategy impossible. In this appendix, we gauge the robustness of our main results with respect to this assumption. To do so, we perform the following exercise: given the calibrated parameters, we solve for the equilibrium lump-sum tax on the output of a firm-worker match that equates the total cost of the unemployment insurance system to the total tax revenue.[1]

Table 1.9 compares the baseline model, as well as the effects of the two reforms, to their counterparts with a fully-financed UI system. Regarding the local deviation from the baseline model, we see very small changes. This is not surprising: total UI costs are 0.4% of GDP in the US, implying a tax rate of 0.46% in terms of average labor output. This small tax leads to a minor reduction in the value of a match, which makes employment less attractive, therefore decreasing E-Pop and LFPR slightly. The same observation is true for both reforms. We view our main conclusions as robust to this extension, since the implied tax rates are very small and the main message of our results does not change.

[1]Note that in this exercise the two reforms do not lead to the same budgetary costs anymore.

E Spline for Home Production by Age

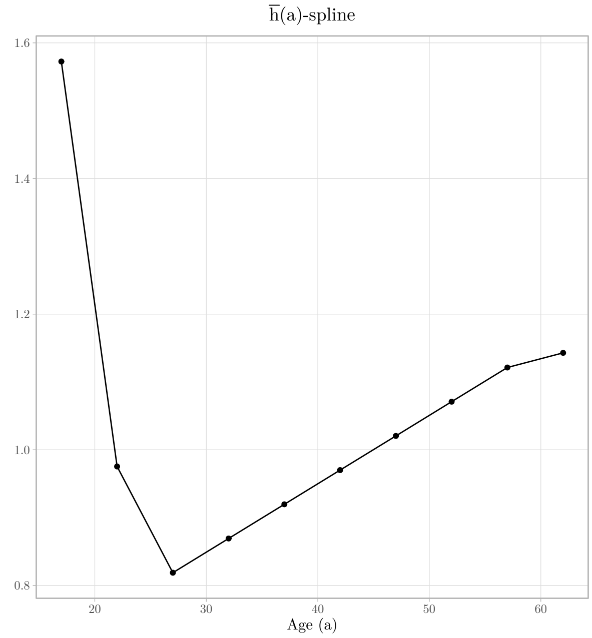


Figure 1.15: Home production by age.

F Response of Flows for Different Age Groups

Moment	Age Group	Baseline Value	UI +17.6% Value	UI +17.6% Pct. Change	99 weeks UI Value	99 weeks UI Pct. Change
JJ	1	0.031	0.029	-5.925%	0.029	-6.943%
	5	0.019	0.019	-2.312%	0.019	-2.534%
	10	0.010	0.010	0.199%	0.010	5.877%
	All	0.021	0.020	-2.316%	0.020	-2.508%
EU	1	0.039	0.044	12.218%	0.042	7.032%
	5	0.009	0.011	13.858%	0.010	6.004%
	10	0.019	0.023	25.202%	0.020	8.143%
	All	0.013	0.015	14.370%	0.014	9.914%
EN	1	0.060	0.057	-3.532%	0.060	0.529%
	5	0.017	0.016	-4.264%	0.017	0.397%
	10	0.057	0.058	2.260%	0.061	6.762%
	All	0.024	0.023	-2.765%	0.024	-0.138%
UE	1	0.219	0.215	-1.956%	0.214	-2.455%
	5	0.245	0.241	-1.931%	0.241	-1.712%
	10	0.186	0.177	-4.726%	0.185	-0.367%
	All	0.234	0.229	-2.047%	0.228	-2.714%
UN	1	0.244	0.239	-2.068%	0.213	-13.027%
	5	0.185	0.185	0.157%	0.166	-10.571%
	10	0.279	0.267	-4.197%	0.196	-29.794%
	All	0.208	0.206	-1.308%	0.179	-14.324%
NE	1	0.048	0.048	0.054%	0.047	-0.908%
	5	0.076	0.076	-0.258%	0.076	-0.600%
	10	0.052	0.051	-0.911%	0.050	-2.600%
	All	0.063	0.062	-0.661%	0.062	-1.719%
NU	1	0.041	0.042	0.514%	0.040	-2.353%
	5	0.054	0.054	-0.775%	0.053	-2.479%
	10	0.000	0.000		0.000	
	All	0.038	0.038	0.592%	0.037	-2.428%

Table 1.10: Effects of more generous UI benefits on different age groups. The table reports how labor market flows for workers belonging to age groups 1, 5, and 10, respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed. Both UI changes imply the same budgetary costs.

G Robustness Exercises

To gauge the robustness of our results with respect to the exogenously set parameters, we re-calibrate the model with different values for the learning parameter α and for the elasticity of the matching function γ.[2] We use two different values for α, one which implies a shorter duration until agents learn their productivity ($\alpha = 1/2$) and one implying a longer duration ($\alpha = 1/6$). Regarding the elasticity of the matching function, we set γ to 0.407 or 1.27 which are taken from Hagedorn and Manovskii (2008) and Den Haan et al. (2000), respectively. Finally, we also consider an alternative target for the level of UI benefits, where we exclude capital income from GDP, since capital is missing in our model. We target UI expenditures over labor income instead, which we compute as UI expenditure / (0.66 · GDP).

Table 1.11 reports the model fit while Table 1.12 shows the effect of a more generous UI system. All alternative calibrations imply very similar results compared to our baseline calibration with respect to the effects on the employment to population ratio, the unemployment rate, and GDP. Moreover, labor productivity is very close to zero in all calibrations. The labor force participation rate exhibits the largest deviations from the baseline calibration with the peak difference for the case of $\alpha = 1/6$. However, this specification has the worst overall data fit with a squared sum of relative deviations twice as high as the other calibrations. Taken together, we conclude that these calibrations support the robustness of our results.

[2] While we restart the global minimization algorithm over 800 times for the baseline calibration, we repeat the procedure over 200 times for each robustness exercise.

Target	Data	Baseline	$\alpha = 1/6$	$\alpha = 1/2$	$\gamma = 0.407$	$\gamma = 1.27$	b/GDP = 0.7%
			Transition Rates				
Flow							
JJ	0.021	0.021	0.020	0.021	0.021	0.021	0.021
EU	0.013	0.013	0.013	0.013	0.013	0.013	0.013
EN	0.024	0.024	0.023	0.025	0.024	0.024	0.024
UE	0.238	0.234	0.237	0.233	0.227	0.241	0.232
UN	0.214	0.208	0.209	0.206	0.199	0.219	0.210
NE	0.063	0.063	0.064	0.063	0.064	0.061	0.063
NU	0.039	0.038	0.039	0.038	0.038	0.038	0.038
			UI System				
b/GDP	0.004	0.004	0.004	0.004	0.004	0.004	0.007
			Tenure Distribution				
Years							
≤ 1	0.072	0.072	0.072	0.072	0.072	0.072	0.072
$(1,3]$	0.229	0.259	0.284	0.242	0.259	0.257	0.257
$(3,9]$	0.227	0.188	0.181	0.197	0.187	0.190	0.188
> 9	0.273	0.280	0.269	0.292	0.278	0.286	0.285
			LFPR				
Age							
15–19	0.271	0.273	0.266	0.269	0.276	0.267	0.270
20–24	0.460	0.463	0.464	0.466	0.469	0.463	0.462
25–29	0.754	0.751	0.768	0.749	0.740	0.766	0.765
30–34	0.830	0.845	0.833	0.846	0.853	0.846	0.838
35–39	0.834	0.852	0.861	0.854	0.863	0.854	0.846
40–44	0.840	0.845	0.876	0.847	0.863	0.845	0.851
45–49	0.847	0.840	0.864	0.838	0.846	0.837	0.844
50–54	0.835	0.816	0.837	0.814	0.825	0.812	0.822
55–59	0.796	0.789	0.808	0.783	0.783	0.783	0.793
60–64	0.709	0.740	0.749	0.731	0.727	0.731	0.741

Table 1.11: Model fit for various calibrations

	Baseline	UI +17.6%		99 weeks UI	
Moment	Value	Value	Pct Change	Value	Pct Change
Main Calibration					
E-Pop	0.704	0.699	-0.732%	0.699	-0.776%
LFPR	0.748	0.746	-0.175%	0.747	-0.018%
U-Rate	0.058	0.063	9.090%	0.065	12.356%
GDP	5.466	5.422	-0.801%	5.420	-0.840%
Labor Prod.	7.759	7.754	-0.069%	7.754	-0.065%
$\alpha = 1/6$					
E-Pop	0.716	0.712	-0.588%	0.713	-0.407%
LFPR	0.758	0.761	0.303%	0.762	0.561%
U-Rate	0.055	0.064	15.130%	0.065	16.404%
GDP	5.043	5.007	-0.716%	5.016	-0.535%
Labor Prod.	7.041	7.032	-0.129%	7.032	-0.129%
$\alpha = 1/2$					
E-Pop	0.701	0.694	-0.997%	0.696	-0.751%
LFPR	0.745	0.741	-0.468%	0.745	0.065%
U-Rate	0.058	0.063	8.553%	0.066	13.143%
GDP	5.105	5.048	-1.121%	5.068	-0.723%
Labor Prod.	7.279	7.270	-0.126%	7.281	0.028%
$\gamma = 0.407$					
E-Pop	0.705	0.701	-0.514%	0.700	-0.578%
LFPR	0.749	0.750	0.065%	0.751	0.256%
U-Rate	0.060	0.065	9.121%	0.068	13.108%
GDP	5.056	5.026	-0.593%	5.024	-0.639%
Labor Prod.	7.176	7.171	-0.079%	7.172	-0.061%
$\gamma = 1.270$					
E-Pop	0.705	0.703	-0.329%	0.702	-0.351%
LFPR	0.746	0.748	0.214%	0.749	0.395%
U-Rate	0.056	0.061	9.218%	0.063	12.633%
GDP	5.521	5.508	-0.237%	5.506	-0.267%
Labor Prod.	7.832	7.840	0.092%	7.839	0.085%
$b/GDP = 0.7\%$					
E-Pop	0.705	0.699	-0.923%	0.699	-0.869%
LFPR	0.748	0.747	-0.209%	0.749	0.148%
U-Rate	0.057	0.064	11.757%	0.067	16.666%
GDP	5.054	5.008	-0.900%	5.012	-0.826%
Labor Prod.	7.167	7.168	0.024%	7.170	0.043%

Table 1.12: Effects of more generous UI benefits across the calibrations. The table reports how flows and stocks respond to a 99 weeks UI extension and an 17.6% increase in UI benefits holding duration fixed. For the baseline calibration, both UI changes imply the same budgetary costs.

Chapter 2

The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare

This chapter is joint work with Almut Balleer, Georg Dürnecker, and Susanne Forstner.

"Optimism is the madness of insisting that all is well when we are miserable."

— Voltaire

1 Introduction

Idiosyncratic labor market risk is a prevalent phenomenon with important implications for individual choices such as wage bargaining (Mortensen and Pissarides (1994)), consumption and saving (Krusell et al. (2010)), job search and job acceptance (Rogerson et al. (2005)), portfolio choice (Den Haan et al. (2017)), and human capital accumulation (Krebs (2003)). Through its influence on individual behavior, labor market risk may affect the processes which shape macroeconomic outcomes such as aggregate employment, physical and human capital accumulation, the distribution of wages, aggregate consumption and inequality in wealth. In labor market research it is common to make use of the rational expectation assumption by imposing that economic agents possess all relevant knowledge about the stochastic processes governing the idiosyncratic risk in the labor market. In this paper, we document in U.S. micro data that agents' subjective probabilities over labor market outcomes systematically differ from their actual ones, and we explore theoretically and quantitatively how this bias in subjective labor market expectations affects both individual decision making and macroeconomic outcomes. Importantly, we report the extent of heterogeneity in the expectation bias across different demographic groups and show that it is a quantitatively important driver of the observed inequality in wealth.

In the first part of the paper, we use data from the Survey of Consumer Expectations (henceforth SCE) to document the subjective expectations of U.S. households about future transitions between the three labor market states employment, unemployment, and out-of-the-labor-force. Most importantly, we find that these subjective transition probabilities differ substantially from the actual probabilities. Specifically, we establish that, on average, households in the U.S. are strongly over-optimistic about their own labor market prospects. That is, households' subjective probability exceeds the respective statistical probability of experiencing a transition into a favorable labor market state –such as finding a job, or remaining employed. At the same time, households tend to underestimate the probability of transitioning into a bad state – such as remaining unemployed, or leaving the labor force. For example, according to our results, unemployed workers overestimate the probability to be employed in four months by 18.8 percentage points, while employed workers underestimate the likelihood of leaving the labor force by 1.9 percentage points. Individuals who are not in the labor force overestimate the probability of entering the labor force by 11.2 percentage points.

Furthermore, we document the heterogeneity in the optimistic bias in expectations across different demographic groups. Most importantly, in this context, we find a strongly negative relation between education and the size of the bias. Accordingly, the optimistic bias is largest for high-school educated individuals, while college-educated individuals –who are still over-optimistic– have more accurate beliefs. For example, unemployed job seekers with a high-school degree overestimate the probability to be employed in fours months by 21.7 percentage points, whereas this number is 10.6 percentage points for job seekers with college degree. Similarly, inactive individuals with high-school education overestimate the likelihood of entering the labor force by 13.8 percentage points, where it is 6.6 percentage points for college-educated individuals.

In the second part of the paper, we perform a theoretical and quantitative analysis. The purpose of this analysis is to explore the extent to which the optimistic bias in labor market expectations affects household life cycle consumption behavior and wealth accumulation and thereby shapes macroeconomic outcomes such as wealth inequality.[1] As part of this analysis, we first use a tractable two-period model to explore in closed form how the bias in expectations distorts the inter-temporal consumption decision of households. In the context of this model, we show analytically that agents with over-optimistic expectations obtain a lower level of lifetime utility than with rational expectations because they save less and, thus, they achieve a lower level of lifetime consumption, and they are overly exposed to random fluctuations in income.

[1]In related work, we use a general equilibrium labor market matching model to study quantitatively the implications of biased labor market expectations on choices of the household related to labor market outcomes. This includes, for example, the decisions of employed workers to leave a job, or of job seekers to search for employment and wage bargaining outcomes (see Balleer et al. (2021)).

Moreover, we show that heterogeneity in the optimistic bias causes differences in savings behavior across agents and thereby leads to inequality in wealth.

In the quantitative analysis, we assess to what extent the empirically observed expectation bias matters for individuals' life cycle consumption, income and wealth, as well as the aggregate distribution of wealth. As part of this analysis, we explore the welfare effects of over-optimism and we briefly discuss the implications of our results for economic policy. As a framework for the quantitative analysis we use a heterogeneous agents life cycle model with incomplete insurance markets, various sources of idiosyncratic risk, and households with different levels of human capital. Crucially, we incorporate households that have a subjective probability distribution over future labor market transitions and we allow the subjective distribution to differ from the actual distribution. Moreover, guided by our empirical findings, we incorporate heterogeneity in the bias across households with different human capital. We calibrate the model to U.S. data and show that the quantitative model matches very well several important data outcomes at the individual and aggregate level. This includes, for example, the life cycle profile of income, consumption and assets for individuals with different levels of human capital, as well as the high degree of inequality in the distribution of wealth in the U.S.

In the final step of our analysis, we examine in a counterfactual experiment the quantitative importance of biased expectations on allocations. In this experiment, we eliminate the bias altogether and assume that all agents in the economy have rational expectations. Then, we compare the characteristics of the implied full information equilibrium with the equilibrium of the baseline economy. The optimistic bias distorts the individuals' inter-temporal consumption allocation and it discourages individual asset accumulation. This effects is particularly pronounced for individuals with low human capital who are more over-optimistic. This effect is quantitatively sizable. For example, the savings rate for high-school educated individuals is, on average, 8 percentage points lower in the economy with biased expectations, whereas for individuals with a college education it is essentially the same as in the economy with full-information. As a result, high-school graduates accumulate less wealth over the life cycle and enter retirement with approximately 33% fewer assets than in the economy without biased expectations. Due to the lack in assets, they attain a lower life cycle path of consumption which implies a welfare loss relative to the full-information case of 5.4% (in terms of equivalent variation in expected lifetime consumption). Naturally, these effects are less pronounced for college-educated individuals who have a much smaller optimistic bias than high-school graduates. As a result, the heterogeneity in the optimistic bias across individuals has a substantial effect on wealth inequality. Without the bias in expectations the wealth Gini coefficient would be 7 percentage points lower. This is an important finding as it suggests that a substantial part of U.S. inequality in wealth distribution is due to the bias in individuals' labor market expectations.

This paper contributes to a growing body of research which collects and uses subjective expectations data to study decision making under uncertainty. See Manski (2004) for an early survey of this literature. Broadly, this literature can be divided into two strands. The first strand examines individual expectations about aggregate variables. This includes individuals' inflation expectations (see e.g. the work by Broer et al. (2021), Carroll (2003), Andolfatto et al. (2008), Malmendier and Nagel (2015), and Coibion et al. (2018), house price expectations (see e.g. Piazzesi and Schneider (2009), Case et al. (2012), and Kuchler and Zafar (2019)), expectations about aggregate unemployment (see Broer et al. (2021), and Kuchler and Zafar (2019)), or expectations about financial market outcomes such as credit spreads, and bond and stock market returns (see Piazzesi et al. (2015), Bordalo et al. (2018), and Vissing-Jorgensen (2003)).

The second strand of literature analyses subjective expectations about individual level variables such as income (see Rozsypal and Schlafmann (2020) and Exler et al. (2020), survival (Grevenbrock et al. (2021)), retirement (Haider and Stephens (2007)), social security benefits (Dominitz et al. (2003)), returns to education (Attanasio and Kaufmann (2014)), and portfolio returns (Vissing-Jorgensen (2003)). As part of this second strand, recent work has started to utilize newly available data to study subjective expectations of individual labor market outcomes. This includes, for example, expectations about job loss, wage offers, and job finding. See Mueller and Spinnewijn (2021) for a recent survey of this literature. Within this literature, several papers are related to ours. First, Mueller et al. (2021) use data from the SCE to compare the perceived and actual job finding for unemployed individuals. Like us, they find that job seekers in the U.S. substantially over-estimate their job finding probability. Moreover, they show in a model of job search how the bias in beliefs induces individuals to engage less in job search and can thereby help understand the slow exit out of unemployment for certain job seekers. In the same vein, Conlon et al. (2018) use the SCE to analyze individuals' expectations and realizations about future wage offers. In particular, they study how individuals update their expectations in response to deviations of realized from expected offers. They embed their empirical findings into a model of job search and show that learning is a key feature to understand the observed patterns of reservation wages. Spinnewijn (2015) analyzes survey data from Price et al. (2006) and finds a substantial optimistic bias of unemployed job seekers. He then studies the implications of this bias for the optimal design of unemployment insurance. Jäger et al. (2021) measure bias in beliefs about outside options of workers and argue that this increases labor market segmentation and lower wages for slow-wage workers. Our work is complementary to these papers in that we analyze not only the job finding expectations of unemployed individuals or employed job seekers, but jointly address the expectations of employed and unemployed workers, as well as non-participants about finding a job or becoming unemployed, or to move out of the labor force. This allows us to obtain a more complete picture of the expectation structure of the working-age population. Moreover, while the aforementioned papers focus on the search behavior of job seekers, we study individual choices with respect to consumption and asset accumulation.

Another related paper is Broer et al. (2021) which proposes a model of information choice to study the effects of biased expectations on macroeconomic volatility and wealth inequality. A key difference to our paper is their focus on expectations about aggregate variables such as inflation and aggregate unemployment. In contrast, we study households' expectations about individual labor market outcomes including job finding, job loss, and transitions to inactivity. Another difference is that, while they document the expectations across wealth quintiles, we explore the variation in the expectation bias across different demographic groups (e.g. education groups) and show that it is a key element for understanding aggregate wealth inequality. Moreover, while they employ a model with infinitely lived agents, we consider a life cycle model with retirement. This allows us to study the effect of biased expectations on the life cycle path of consumption and assets, and on retirement savings.

Our paper also contributes to the literature studying the determinants of inequality in wealth. See De Nardi and Fella (2017) for a recent survey of this literature. According to De Nardi and Fella (2017) it remains a challenge in this literature to reconcile the predictions of the canonical Bewley model (Bewley (1977)), which serves as the workhorse model to study wealth inequality, with the empirically observed patterns of individual saving behavior and wealth accumulation. Specifically, while in the U.S. wealthy individuals save considerable amounts of their income, the Bewley model counterfactually predicts savings rates to decrease with wealth and to even turn negative if net worth is sufficiently large relative to labor earnings.[2] As a result, a number of additional savings motives were introduced to improve the empirical fit of the model. The set of savings motives includes, for example, bequests, preference heterogeneity, entrepreneurship, or medical expense risk. Our analysis adds to this literature by showing (i) that the bias in subjective labor market expectations is a quantitatively important determinant of individual saving behavior, and (ii) that the empirically observed heterogeneity in the bias across individuals generates differences in the saving behavior, which are in line with those observed in the data. More concretely, in the presence of the expectation bias our quantitative model generates a strong positive association between wealth and saving rates. Furthermore, our anal-

[2]In the Bewley model, agents engage in precautionary savings in the presence of idiosyncratic income shocks. Thus, the ability to self-insure increases with wealth and the precautionary savings motive looses relevance.

ysis helps to understand the determinants of wealth inequality. As mentioned above, we establish in the quantitative analysis that a substantial part of the significant inequality in U.S. wealth distribution is due to the optimistic bias in individuals' labor market expectations. As an important corollary, we show that without biased expectations the model cannot generate the high dispersion of wealth observed in the data.

The remainder of the paper is structured as follows. In Section 2 we document the facts about subjective labor market expectations in the U.S. In Section 3.1 we present a simple two-period model to illustrate how biased expectations affect individual decision making regarding consumption and savings. In Sections 3.2 and 4.1 we set up and calibrate the quantitative model. In Section 4.2 we first explore the quantitative properties of the calibrated model and then we perform the main quantitative experiment. Section 4.5 discusses the robustness of our results and Section 5 concludes.

2 Facts about Biased Labor Market Expectations

2.1 Aggregate

We use data from the New York-Fed's *Survey of Consumer Expectations* to measure the subjective probabilities of U.S. individuals to experience a change in their labor market state. The SCE, which launched in 2013, is a nationally representative survey of a rotating panel of approximately 1,300 households. It focuses primarily on subjective expectations about a number of macroeconomic and household-level variables.[3] The SCE has several components. We make use of the data provided by the 07/2014-11/2019 waves of the *Labor Market Survey*. In this survey, respondents are asked to report their expectations about several labor market outcomes that pertain to them. More precisely, the question in the survey that is relevant for our purpose reads: *"What do you think is the percent chance that four months from now you will be ...*

[1] employed and working for the same employer

[2] employed and working for a different employer

[3] self-employed

[4] unemployed and looking for work

[5] unemployed and not looking for work?

We aggregate [1]-[3] into one state of employment. Moreover, corresponding to the usual notion of unemployed and non-participants used in the literature, active job search is the key characteristic that distinguishes unemployed individuals from non-participants. Hence, we classify [4] as the state of unemployment and [5] as the

[3]For an introduction to the SCE see Armantier et al. (2016).

state of not in the labor force. The labor market states among the response options are mutually exclusive and exhaustive. Indeed, for the majority of respondents the sum of probabilities across the three states adds up to one. We exclude the few observations (22) for which the sum is not equal to one.

A key feature of the SCE is its reliance on a probabilistic question format. This allows us to aggregate the answers across individuals and report the average subjective probability for specific sample of individuals. We select individuals aged 25-60 years who do not attend school or college. The baseline sample then consists of 12,392 observations. See Table 2.16 in Appendix A for the descriptive statistics of the sample. In the first step, we compute the subjective probabilities separately for employed and unemployed individuals, as well as for non-participants.[4] The results are in Table 2.1 in the columns labeled ”Subjective”. We also report in the table the implied standard errors. The rows in the table represent the current labor market state of an individual and the columns represent the future (expected) labor market states. According to our results, employed workers expect to be employed with a probability of 96.1%, unemployed with 2.5%, and not in the labor force with 1.4% in four months after the interview.

We now compare these subjective probabilities to the actual probabilities. To shed light on this question, we use observations from the Current Population Survey (CPS) on individual labor market transitions to compute the implied actual labor market transition probabilities.[5] To achieve a high degree of consistency between subjective and actual probabilities from the two datasets, we apply the same sample selection criteria to the two datasets and use the same definitions of labor market states and transitions. Appendix A.2 contains the details. As before we consider the three states: employment, unemployment, and not in the labor force. To be concrete, we compute the actual transition probability between labor market states s and s' as the fraction of individuals who where in state s in a given month and are in state s' four months later. Moreover, to be consistent with the subjective probability measure we do not consider labor market transitions in the CPS that take place in between a four months period. This is because the SCE asks explicitly about the probability to be in a given state in four months and not about the probability to experience a labor market transition within the next four months.

Clearly, for the comparison of the actual and the subjective transition probabilities to be meaningful, we require the composition of the two samples (taken from the CPS and SCE) to be similar in terms of demographic characteristics. Even though both surveys are designed to be nationally representative, the two samples may differ in terms of composition due to, for example, different sampling or non-random attrition.

[4] The details of these calculations, including the definition of labor market states and sample selection criteria are in Appendix A.1.

[5] The CPS data are extracted from the IPUMS data repository; see Flood et al. (2020).

	Subjective			Actual			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. *E*: employment, *U*: unemployment, *N*: not in the labor force. Example: ”UE” represents the expectation of unemployed workers to be employed in four months.

Table 2.1: 4-Months subjective and actual transition probabilities

Consequently, if we used the sample weights provided by each survey to aggregate the individual responses then the implied results would be subject to a composition bias. To avoid such bias, we use the sample weights provided by the CPS to aggregate the individual observations from the SCE. The details of these calculations can be found in Appendix A.2.[6]

The results for the actual labor market transition probabilities together with the implied standard errors are in Table 2.1 in the columns labeled ”Actual”. In addition, we also report in the table the difference between subjective and actual probabilities. We will refer to this differences as the individuals' bias in their subjective labor market expectations. A number of observations are worth highlighting. First, employed workers tend to over-estimate the probability of remaining employed. The subjective probability of being employed in four months is 96.1% whereas the actual probability is 95.2%. The standard errors around the two probabilities are very small; hence, the difference of 0.9 percentage points between the subjective and the actual probability is statistically significant at the 1% level. Moreover, the results in the table indicate that in case of job loss, workers underestimate the likelihood of leaving the labor force by 1.9 percentage points. This difference is highly significant. Another important finding is that unemployed individuals vastly over-estimate their re-employment prospects.[7] Job seekers expect to be employed in four months with a probability of 61.3%. This is 18.8 percentage points above the actual employment probability. At the same time, unemployed workers substantially underestimate the likelihood of leaving the labor force by a remarkable 18.7 percentage points. Furthermore, our results show that individuals who are not in the labor force, generally over-estimate the probabil-

[6]In Table 2.18 we report the results obtained when the weights from the SCE are used. The patterns are qualitatively the same as in the baseline case; even quantitatively the differences are small.

[7]This result is in line with Mueller et al. (2021) who also find evidence of an optimistic bias of unemployed workers. Likewise, Conlon et al. (2018) find in the SCE that job seekers are generally over-optimistic about future wage offers.

ity of entering the labor force by 11.2 percentage points. While they correctly assess the probability of employment, they strongly over-estimate the likelihood of starting to look for a job. The pattern emerging from Table 2.1 suggests that individuals in the U.S. are generally over-optimistic about their own labor market prospects. More specifically, individuals tend to underestimate the likelihood of experiencing a transition into bad labor market states (for example, $E \to N$, $U \to N$) and they overestimate the likelihood of moving to good states ($U \to E$, $N \to \neg N$).[8]

At this point it is important to discuss the robustness and the generality of these findings. In our baseline, we compute the actual transition probabilities from the CPS and not the SCE. This choice is mainly motivated by sample size. The CPS is a large-scale survey with monthly information on roughly 120,000 respondents. As a result, we observe a large number of individual labor market transitions and this allows us to obtain precise estimates of the transition probabilities. In contrast, in the SCE we observe a much lower number of individual labor market transitions than in the CPS, and thus, the implied estimates of actual transition probabilities obtained from the SCE are somewhat imprecise.[9] Table 2.19 reports the results when the actual transition probabilities are computed from the SCE. The smaller number of observed transitions in the SCE is reflected by the sizable standard errors. Reassuringly, the qualitative patterns for the bias in expectations are very similar to those obtained in the baseline.

An often-raised concern regarding data on subjective expectations addresses the reliability of such data due to both systematic and differential difficulties in in the cognitive ability of individuals to deal with probabilities. First, if the assessment of probabilities is systematically biased in a certain way, e.g. if subjective probabilities are generally over-estimated, it is still valid to investigate the comparison of the relative bias across groups. Second, to address this concern, we use a set of control questions in the SCE, which are meant to assess the respondents' ability to calculate and process probabilities.[10] More concretely, we calculate the bias in subjective expectations separately for those individuals who correctly answer all control questions, and those individuals who give a wrong answer to at least one question. The results are in Table 2.20. The qualitative patterns are very similar between the two groups

[8] The only exception from this pattern is the transition from employment to unemployment, about which workers are overly pessimistic. In Balleer et al. (2021) we use data from the German Socio-Economic Panel to document the expectations of employed workers and unemployed job seekers in Germany. Like in the U.S., workers are overly pessimistic when transitioning from employment to unemployment, but unlike in the U.S. this pessimism also applies when transitioning from employment to non-participation. For job seekers we find an optimistic bias in their job finding expectations, which is similar to the pattern in the U.S.

[9] Notice that the number of transitions observed in the SCE (6,180) is also significantly below the number of observations from which we compute the subjective transition probabilities (12,392). This is because the calculation of the actual probabilities requires us to observe individuals in two consecutive waves of the labor market module.

[10] See Appendix B for the list of control questions in the survey.

and any differences in the value of the bias are minor. Generally, these findings alleviate the concern that individuals who are better able to deal with probabilities also have a more precise perception of their labor market risk.

Lastly, we address the important question of whether U.S.-workers' over-optimism is a stable phenomenon over time or it applies only to specific years. As a first step, we compute the actual and the subjective transition probabilities separately for each year from 2014-2019. The results in Table 2.21 confirm that the baseline findings also hold year-by-year. As to whether over-optimism is a long-run phenomenon, the SCE cannot provide a definitive statement due to its relatively short time frame. However, we can resort to earlier data on labor market expectations from the U.S. Survey of Economic Expectations (SEE), which was conducted between 1994-2002. Even though the SEE differs from the SCE in terms of design and survey questions, we can nevertheless compare individuals' subjective expectations about job loss with the actual counterparts. See Appendix C for the details. Reassuringly, we find that workers' over-optimism has been present consistently throughout the entire time period covered by the SEE. Interestingly, this time frame also includes a period of an economic downturn (in year 2001), during which, however, we do not observe a reversal in the observed bias in subjective labor market expectations.

2.2 Heterogeneity

In the next step, we explore whether the findings of the previous section generally hold across different population groups or whether there is noteworthy heterogeneity in the population in terms of the sign and the degree of the bias in expectations. To this end, we consider different demographic groups. In particular, we disaggregate the data according to gender, age, education, and income and compute the subjective and the actual transition probabilities for each group separately (see Tables 2.22 – 2.25 in Appendix D). The results for gender do not indicate any systematic differences between men and women. If anything, women tend to be slightly more over-optimistic than men. With respect to age, we find some evidence for a decrease in the level of the bias with age, indicating that young workers have a less accurate perception of their labor market situation than prime-age workers. However, this pattern is not significant, primarily because the small number of observations for each age group implies large standard errors around the subjective transition probabilities.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
All	0.9	1.0	-1.9	18.8	-0.1	-18.7	0.0	11.2	-11.2
	(0.17)	(0.11)	(0.11)	(2.27)	(1.85)	(1.25)	(0.80)	(1.04)	(1.41)
High school or less	1.8	0.7	-2.5	21.7	-2.8	-18.9	1.3	12.4	-13.8
	(0.45)	(0.29)	(0.26)	(4.26)	(3.27)	(2.44)	(1.40)	(1.88)	(2.51)
Some college	0.9	0.8	-1.6	21.4	0.1	-21.5	-0.3	10.4	-10.2
	(0.26)	(0.15)	(0.19)	(2.78)	(2.56)	(1.15)	(0.92)	(1.01)	(1.48)
College and higher	0.3	1.2	-1.5	10.6	4.8	-15.4	-2.8	9.4	-6.6
	(0.13)	(0.09)	(0.09)	(2.67)	(2.52)	(1.01)	(1.15)	(1.07)	(1.70)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months.

Table 2.2: Expectation bias in 4-months transition probabilities (by education)

Interestingly, we find a systematic relationship between education and the level of workers' over-optimism.[11] More concretely, we split the sample into three education groups: low-skilled, medium-skilled and high-skilled individuals. We define low-skilled individuals as those who have at least a high school degree, middle-skilled as those with a high school degree, but no college degree, and high-skilled as those with at least a college degree. To keep the exposition concise, we report in Table 2.2 for each education group only the difference between the subjective and the actual transition probabilities. The probability levels and their standard errors can be found in Table 2.22 in Appendix D. Importantly, the results in the table reveal that the level of over-optimism is decreasing in the skill level. In other words, high-skill individuals tend to have a more precise perception of their labor market perspectives than low-skill individuals. This pattern applies to almost every labor market transition and it is particularly pronounced for unemployed workers and non-participants. For example, job seekers who are low-skilled overestimate the probability to be employed in four months by 21.7 percentage points. In contrast, for the high-skilled the difference between the subjective and the actual reemployment probability is only half of that and equal to 10.6 percentage points. We find a similar pattern among non-participants, where all skill groups, but particularly the low-skilled individuals, are over-optimistic

[11]This result is complementary to previous findings in the literature showing that the accuracy of beliefs is positively associated with individual income, wealth, or experience. For example, Exler et al. (2020) show in SCF data that financially less literate individuals have less precise expectations about future income, and they tend to underestimate the probability of experiencing bad income realizations. Broer et al. (2021) find in the SCE that wealthier households in the U.S. have more precise expectations about inflation and aggregate unemployment. Another example is Vissing-Jorgensen (2003) who find that investors are generally optimistic about stock market returns but the bias in beliefs is smaller for more wealthy investors. She finds the same pattern for investors' age, where the young are more optimistic than experienced investors.

about entering the labor force. The low-skilled over-estimate the probability by 13.8 percentage points, whereas the number for the high-skilled is only half of that and equal to 6.6 percentage points. Lastly, among employed workers, the low-skilled over-estimate the probability of being employed four months later by 1.8 percentage points, whereas for the high-skilled the subjective reemployment probability is almost in line with the actual probability.[12]

The expectation biases reported in Table 2.2 are based on the average expectations of all individuals belonging to the same education group. One may be concerned that these biases are blurred by compositional differences across education groups, or by potential dependencies between education and other individual characteristics. We address this concern in the following empirical analysis. In the first step of this analysis, we estimate the Probit model, $P(Y_i = 1|x_i) = \Phi(x_i'\beta_Y)$, in order to predict the probability of an individual to experience a given labor market transition, Y, conditional on the observable variables x. The set of possible transitions includes $Y \in \{EE, EU, EN, UE, UU, UN, NE, NU, NN\}$. As an example, consider the UE-transition. The outcome variable Y is equal to one, if we observe an individual moving from unemployment to employment, and it is equal to zero otherwise. The characteristics we include in x control for age, gender, race, income, and year fixed effects. Moreover, we include in x a set of dummy variables to represent our education groups from above. We use data from the CPS on actual individual labor market transitions to estimate the coefficients β_Y separately for each type of transition. The estimated coefficients are used to compute for each individual observed in the SCE the predicted actual labor market transition probability. That is, we evaluate the estimated Probit model using in X the individual's characteristics, and obtain the predicted probability as the fitted value from the model. Next, we subtract the predicted actual probability from the individual's reported subjective transition probability to compute the individual's expectation bias. Lastly, we estimate by OLS the linear model $z_{iY} = x_i'\gamma_Y$, where z_{iY} is the expectation bias of individual i with respect to the transition Y. The vector x_i contains the same control variables as in the Probit estimation.

In Table 2.3 we report the implied expectation bias by education group. The bias is computed as the average marginal effect for each education group, where all other control variables are set to their respective mean value.[13] Clearly, the expectation biases would be identical to those in Table 2.2 when we included in X only the education dummies. Hence, any difference to the previous results conditions on other variables

[12] We also explore the relationship between individual income and the bias in subjective expectations. Not surprisingly, since income and educational attainment are strongly correlated, we find very similar patterns for income groups as for education groups. That is, individuals with low income are strongly over-optimistic, whereas high-income individuals have more precise expectations. See Table 2.25 for the results.

[13] Appendix E provides further details of the empirical procedure.

	EE	EU	EN	UE	UU	UN	NE	NU	NN
High school or less	2.4	0.5	-2.8	23.7	-2.4	-21.5	1.3	11.9	-13.1
	(0.42)	(0.27)	(0.26)	(3.42)	(2.72)	(1.81)	(1.28)	(1.63)	(2.15)
Some college	1.0	0.6	-1.7	22.3	0.1	-22.4	0.3	10.1	-10.4
	(0.25)	(0.14)	(0.18)	(2.70)	(2.45)	(1.17)	(0.92)	(0.97)	(1.43)
College and higher	0.2	1.4	-1.6	13.0	4.0	-17.0	-0.8	11.7	-10.9
	(0.17)	(0.12)	(0.10)	(2.78)	(2.60)	(0.99)	(1.28)	(1.37)	(1.96)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months.

Table 2.3: Expectation bias in transition probabilities (conditional, by education)

controls for compositional differences of, e.g., age, race, income or year between the education groups. Most importantly, the expectation biases we obtain after controlling for worker observables are very similar to those in Table 2.2. Specifically, we can confirm the positive expectation bias among individuals, as well as the robustly negative relationship between the level of over-optimism and education.

2.3 Learning

Lastly, we address the question whether and to what extent individuals learn over time and form increasingly accurate labor market expectations. While this is certainly a relevant question to ask in the context of expectation biases, there are several reasons why it is not straightforward to address it. First, the SCE offers a relatively short panel dimension and follows an individual for a maximum of 12 months. Within this narrow time frame, respondents are asked only every four months to report their subjective transition expectations. At the same time, the attrition of survey participants is high. As a result, we observe for only 17% of individuals in our sample more than two interviews in which respondents report their transition expectations. With such limited information at hand we refrain from analyzing expectation updating at the individual level. An alternative way to explore learning is to make use of the time dimension embedded in cross-sectional information. For example, learning may be inferred from the variation in the expectation bias across individuals with different job tenure, or unemployment duration. A decline in the (absolute value of the) bias with increasing duration may be interpreted as individual learning. We proceed along these lines and extend the previous empirical analysis to include in the regression as additional control variables individual job tenure, unemployment duration, and dura-

Ten	EE	EU	EN	U_{dur}	UE	UU	UN	N_{dur}	NE	NU	NN
<3 m	5.3	-0.6	-4.7	0-3 m	16.6	-1.4	-15.0	0-12 m	-15.6	9.9	6.1
	(1.04)	(0.77)	(0.55)		(3.52)	(2.25)	(3.06)		(2.37)	(2.15)	(3.12)
3-6 m	2.3	0.4	-2.7	4-6 m	23.7	-4.3	-19.6	>12 m	7.7	14.0	-21.7
	(0.84)	(0.77)	(0.22)		(7.65)	(5.05)	(4.03)		(1.89)	(1.80)	(2.63)
6-12 m	1.6	-0.2	-1.4	7-12 m	36.1	-7.6	-29.0				
	(0.58)	(0.32)	(0.41)		(2.89)	(3.93)	(1.91)				
1-5 y	0.3	0.8	-1.0	>12 m	32.8	-1.0	-34.0				
	(0.21)	(0.14)	(0.13)		(6.99)	(4.88)	(3.05)				
>5 y	-0.5	1.2	-0.7								
	(0.16)	(0.10)	(0.10)								

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. *E*: employment, *U*: unemployment, *N*: not in the labor force. *XY*: Transition from current labor market state *X* to future state *Y*. Example: "UE" represents the bias of unemployed workers' expectation to be employed in four months. *Ten*: Tenure of current job, in months (m) and years (y). U_{dur}: Duration of current unemployment spell, in months (m). N_{dur}: Duration of current non-employment spell, in months (m).

Table 2.4: Conditional expectation bias, by duration

tion of non-participation. In Table 2.4, we report the implied conditional expectation biases for all nine labor market flows and different durations.[14]

The results in the table reveal a somewhat mixed pattern. The expectation bias of employed workers to stay employed (EE) and to leave the labor force (EN) decreases with job tenure. Since, generally, job security increases with job tenure and hence EE flows are more and EN flows are less likely, this suggests constant beliefs about labor market transitions out of employment of employed workers. However, there is no clear relationship between job tenure and the expectation bias of becoming unemployed (EU). For unemployed workers, the expectation bias to become employed (UE) and to leave the labor force (UN) increase with unemployment duration. The pattern is less clear for remaining unemployed (UU). This result is consistent with the findings of Mueller et al. (2021) who use a different question in the SCE and establish that unemployed workers are generally over-optimistic about their job finding prospects and that they do not revise their beliefs downward when remaining unemployed. Since, as is well known, the job finding hazard gradually declines with unemployment duration, this, again, suggests constant beliefs about labor market transitions of job seekers. The learning pattern for individuals who are out of the labor force is generally ambiguous. While the beliefs about finding employment (NE) become more precise, the expectation bias related to entering job search (NU) increases with duration. Overall, non-participants tend to form increasingly less accurate beliefs about remaining out of the labor force (NN).

[14] A detailed description of the analysis is in Appendix F.

In the last step, we consider individuals' age as the relevant time dimension and we explore whether individuals learn as they grow older. For this purpose, we make use of the Probit analysis from above to compute the conditional expectation bias for different age groups. We report the results in Table 2.32. As before, the pattern is not clear-cut. For some labor market transitions (EE, EN, NE, NU) the bias tends to decline with age, but for other transitions (EU, UE, UN) the bias increases or shows no systematic variation. In Appendix G, we use yet another set of expectation questions from the SCE to provide more analysis of learning, and we obtain qualitatively similar findings.

Taken together, our analysis reveals no clear-cut evidence of individuals systematically learning about the relevant labor market transitions. As a consequence, we choose not to incorporate the feature of learning into our theoretical framework. Looking ahead, in the quantitative analysis we are primarily interested in the implications of biased labor market expectations on aggregate long-run outcomes, such as the distribution of wealth. For this purpose, it is rather inconsequential whether and to what extent individuals update their expectations over time.

3 Model

Motivated by our empirical findings, we proceed to explore the effects of individuals' over-optimism on individual decision making and macroeconomic outcomes. In the first step of our analysis, we lay out a stylized two-period general equilibrium model in order to illustrate theoretically how a positive bias in subjective labor market expectations shapes individual choices of consumption and asset holdings, and thereby affects aggregate wealth inequality. The purpose of the simple model is to provide a conceptual framework that allows for an analytical characterization of the main forces at work. The main insights of this analysis will be useful for the interpretation of the results of the quantitative analysis that we perform in Section 3.2. In this analysis, we use a calibrated general equilibrium model to explore to what extent the observed differences between subjective and actual labor market expectations matter quantitatively for individual life cycle profiles of asset accumulation and consumption, as well as welfare and wealth inequality.

3.1 Two-Period Model

The model economy is populated by a unit mass of risk averse individuals who live for two periods. In the first period, every individual is employed and receives deterministic income $0 < y_1 < \infty$. Income in the second period, y_2, depends on an individual's labor market state. With (true) probability $p > 0$, an individual is employed and receives income $y_2 = \bar{y}$. With (true) probability $1 - p$ the individual has no job in the second period and receives income $y_2 = \underline{y} > 0$; where $\underline{y} < \overline{y}$. Individuals know the values of $\underline{y}$ and $\overline{y}$ but they have subjective expectations about the realizations of the labor market states. These subjective expectations are given by $(p + \Delta)$ and $(1 - p - \Delta)$, respectively. Δ denotes the degree of the individual's bias in expectations and $\Delta > 0$ represents the case of over-optimism. Moreover, we assume that individuals start with zero initial assets but they can save part of their first-period income and consume it in the second period. The period budget constraints are

$$c_1 + k = y_1 \qquad\qquad c_2 = y_2 + rk$$

where c_1 and c_2 denote period consumption, k is savings and r is the interest rate. Agents live for two periods, hence, they do not leave any capital for after their demise. Let $u(c)$ denote the agent's period utility function and assume that it satisfies the usual regularity and Inada conditions. We assume that there is a firm which –in the second period only– rents capital and produces output. All markets are competitive. Using the period budget constraints and assuming time-separable utility, we can formulate the agent's expected utility maximization problem

$$\max_{0 \leq k \leq y_1} u\big(y_1 - k\big) + \beta(p + \Delta)u\big(\overline{y} + rk\big) + \beta(1 - p - \Delta)u\big(\underline{y} + rk\big)$$

where $0 < \beta < 1$ is the personal discount factor. The associated Euler equation reads

$$\beta r\Big[(p + \Delta)u'(\overline{y} + rk) + (1 - p - \Delta)u'(\underline{y} + rk)\Big] = u'(y_1 - k)$$

A unique interior k with $0 < k < y_1$ exists iff $\beta r\big((p + \Delta)u'(\overline{y}) + (1 - p - \Delta)u'(\underline{y})\big) > u'\big(y_1\big)$. This condition holds and agents' savings are positive if, for example, the interest rate is sufficiently large relative to agents' impatience $r > 1/\beta$, or the bad realization of income $\underline{y}$ is sufficiently small which induces agents to self-insure. Next, we use the Euler equation to demonstrate how the optimal savings choice is affected by the bias in expectations Δ. To this end, we compute $\frac{dk}{d\Delta}$, keeping the interest rate r constant. After a few lines of algebra, we obtain

$$\frac{dk}{d\Delta} = \frac{u'(\underline{y} + rk) - u'(\overline{y} + rk)}{u''(y_1 - k)/(\beta r) + r(p + \Delta)u''(\overline{y} + rk) + r(1 - p - \Delta)u''(\underline{y} + rk)}$$

Since $\underline{y} < \overline{y}$, $u' > 0$ and $u'' < 0$, we obtain that $\frac{dk}{d\Delta} < 0$. This is a standard result in expected utility theory going back to the work by Bernoulli (1738) and Savage (1954). It says that over-optimism, represented by $\Delta > 0$, induces agents to build up less precautionary savings. An immediate implication is that over-optimistic agents,i.e., those who underestimate the probability of receiving a bad income realization, engage less in self-insurance and are more exposed to income fluctuations than rational agents (for whom $\Delta = 0$). This is reflected by the fact that the difference in second-period utilities between the good state and the bad state, $u(\overline{y} + rk) - u(\underline{y} + rk) > 0$, is increasing with Δ. Moreover, it is straightforward to show that, if an interior solution exists, consumption in the second period, c_2, and total lifetime consumption $(c_1 + c_2)$ decrease with Δ irrespective of the realization of income in the second period. That is, individuals with a positive bias in their subjective expectations enjoy a lower level of total consumption and of welfare as measured by the discounted sum of lifetime utility.

Next, we derive the implications for the equilibrium interest rate. For concreteness, we assume that a fraction $0 < \phi < 1$ of the population is over-optimistic and has $0 < \Delta < 1 - p$, whereas the remaining fraction $(1 - \phi)$ of the population has correct beliefs ($\Delta = 0$). Therefore, aggregate capital, K, in the economy is given by

$$K = (1 - \phi)k^r + \phi k^o$$

where k^r and k^o are the capital holdings by the realist and the optimist individual, respectively. The result from above implies that $k^r > k^o$. Let $F(K)$ denote the production technology of the firm with $F'(K) > 0$ and $F''(K) < 0$. With competitive pricing, we obtain the usual interest rate rule $r = F'(K)$. To explore the aggregate effects of a bias in expectations, suppose that $\Delta = 0$ for both types of agents. An increase in Δ for the optimist leads to a reduction in k^o. This reduces aggregate capital K and leads to an increase in the interest rate r. A higher interest rate affects agents' savings choice. The sign of $\frac{dk}{dr}$ depends on the functional form of $u(\cdot)$. For example, with log-utility we get that $\frac{dk}{dr} > 0$, which implies that both types of agents save more and this partly offsets a lower capital choice of the optimist agent.

To sum up, our analysis reveals the following insights: First, over-optimistic agents hold fewer assets than rational agents; hence, a positive bias in expectations for some individuals per se leads to wealth inequality. Lower savings imply a lower aggregate capital stock and a higher equilibrium interest rate. Looking ahead to the full model, these results imply that wealthier individuals enjoy higher asset returns and, hence, they can benefit from the bias of the optimistic agents. This channel further amplifies aggregate wealth inequality. A similar effect materializes in the full model where wages are endogenous. A lower aggregate capital stock lowers the marginal product of labor and thereby depresses wages. This hits primarily the asset-poor individuals whose primary income source is labor earnings. Second, our findings imply that less self-insurance due to over-optimism impedes individual's ability to smooth consumption across states and over the life cycle.

3.2 Full Model

In this section, we present the full model that we use in our quantitative analysis. The theoretical framework builds on the canonical Bewley–Huggett–Aiyagari model, and it shares many features of the stationary version of the model in Krueger et al. (2016); henceforth KMP. In a nutshell, the agents in our model economy have a life cycle including working-age and retirement, they have different levels of human capital, and they face idiosyncratic labor market risk. Insurance markets are incomplete and agents accumulate assets to self-insure against labor market risk and longevity risk, and to save for retirement. Agents have a subjective probability distribution over individual labor market states and this distribution can differ from the actual probability distribution. Aggregate output is produced by a representative firm that rents capital and labor from households at competitive factor prices. In equilibrium, individuals' asset holdings are characterized by a stationary non-degenerate distribution function.

Lifecycle

We follow KMP and assume that individuals are either working-age (denoted by W) or retired (denoted by R). The age of an individual is denoted by $j \in \{W, R\}$. With the constant probability $1-\theta$ working-age individuals retire, and with probability $1-\nu$ retired individuals die. Deceased individuals are replaced by new working-age individuals. Stochastic aging and death imply that the population shares of both types of individuals are given by:

$$\Pi_W = \frac{1-\nu}{1-\theta+1-\nu} \qquad \Pi_R = \frac{1-\theta}{1-\theta+1-\nu}$$

Preferences and Assets

We assume that an individual's preferences are given by a CRRA utility function over current consumption:

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

where $\sigma > 0$. As is standard, we assume that insurance markets are incomplete, but as a means of self-insurance, agents can accumulate assets, denoted by $a > \bar{a}$, which yield a non-state-contingent return, denoted by r. $\bar{a} \geq 0$ is a borrowing constraint. Individuals are born with zero assets.

Human Capital

Individuals are ex-ante heterogeneous with respect to human capital. We introduce differences in human capital across individuals because we want our model to capture the empirical finding of Section 2 that the size of the bias in subjective expectations varies substantially across education groups. A worker's level of human capital is denoted by h. We allow for three levels of human capital: low-skill, (h_L), medium-skill, (h_M), and high-skill, (h_H). h is assumed to stay constant over time and, hence, there is a constant population share for each h-type, given by $P(h)$, with $\sum_h P(h) = 1$. At birth, workers draw their human capital level according to the stationary probabilities $P(h)$.

Idiosyncratic Employment Risk

We assume that a working-age individual can be either employed, unemployed, or not in the labor force. Idiosyncratic transitions between labor market states are stochastic and governed by transition probabilities that are denoted by $p_h(s'|s)$. In particular, $p_h(s'|s)$ is the actual per-period probability that a worker with human capital level h will transit from state s to state s', where $s, s' \in \{\boldsymbol{e}(mployed), \boldsymbol{u}(nemployed), \boldsymbol{n}(ot\ in\ the\ labor\ force)\}$ denotes the labor market state. The invariant distribution of s among workers with human capital h is given by $P_h(s)$, with $\sum_s P_h(s) = 1$.

Two aspects of our modeling of the labor market deserve further explanation. First, we allow the transition probabilities to differ across workers with different levels of human capital. This choice is motivated by the empirical observation that actual labor market transition rates differ substantially across workers with different levels of education. We want the model to be flexible enough to capture this empirical feature. Second, we depart from the conventional way to consider only employment and unemployment as labor market states, and instead we also allow individuals to be not in the labor force. This approach has several advantages: (i) in the data the flows in and out of the labor force are just too big to ignore; (ii) having three labor market states allows for a precise mapping of the model to the data on individual labor market expectations which features the same three states; (iii) being out of the labor force is a fundamentally different state for an individual in terms of income and job finding prospects than being in unemployment. Hence, we want the model to be able to capture the potential individual expectation bias of the probability of being in this labor market state.

Idiosyncratic Labor Productivity

We follow KMP and introduce idiosyncratic labor productivity risk. An individual's labor productivity, denoted by z, is stochastic and governed by a first-order Markov process. $\pi_h(z'|z)$ is the conditional probability that a worker with human capital h will transit from state z today to state z' tomorrow. The invariant distribution of z for workers with human capital h is $\Pi_h(z)$. Given the focus of our analysis it is useful to include productivity risk into the model because it allows us to obtain a realistic representation of individual labor income processes and, thus, we are able to match the degree of actual labor market risk that individuals face. Moreover, as shown by KMP, idiosyncratic productivity is the key feature for matching the observed wealth distribution.

Production

A representative firm rents capital from households and hires labor to produce output with the production function:

$$F(K,N) = K^{\alpha}N^{1-\alpha}$$

where $\alpha \in [0,1]$. K denotes aggregate capital (defined below). N denotes total labor in efficiency units which is computed as the sum of all employed workers' effective labor supply

$$N = \Pi_W \sum_h P_h P_h(e) \sum_z \Pi_h(z) hz$$

where Π_W is the total mass of working-age individuals, P_h is the fraction of individuals with human capital h, $P_h(e)$ is the fraction of individuals with human capital h who are employed, and $\Pi_h(z)$ is the fraction of workers with human capital h that have productivity z. Since, $\sum_z \Pi_h(z) = 1$, the term $\Pi_W \sum_h P_h P_h(e)$ represents aggregate employment.

Factor markets are competitive, which implies the usual marginal product pricing

$$r = F_K(K,N) = \alpha\left(\frac{K}{N}\right)^{\alpha-1} \qquad w = F_N(K,N) = (1-\alpha)\left(\frac{K}{N}\right)^{\alpha} \tag{2.1}$$

w is the wage per efficiency unit of labor.

Optimization Problem of a Retired Individual

Retirees earn income on their asset holdings and they collect social security payments. In particular, we assume that social security benefits, denoted by $b_{ss}(h)$, are a fixed fraction $\rho_{ss} \in [0,1]$ of the average wage of a worker with the same human capital.

$$b_{ss}(h) = \rho_{ss} wh \sum_z \Pi_h(z) z$$

That is, pension benefits depend only on the individual's human capital but not on her actual history of past contributions.[15] Moreover, we follow KMP and assume

[15] The decoupling of benefits from actual contributions helps to keep the state space at a manageable size.

that households have access to perfect annuity markets which implies that the assets of the deceased individuals are used to pay an extra return of $1/\nu$ to the retired survivors. A retired individual with asset holdings a and human capital h chooses current-period consumption c and next-period's assets a' to solve the inter-temporal utility maximization problem

$$W^R(a,h) = \max_{a'} \left\{ u(c) + \nu\beta W^R(a',h) \right\} \tag{2.2}$$

subject to

$$c + a' = (1+r-\delta)\frac{a}{\nu} + b_{ss}(h) \qquad \text{and} \qquad a' \geq \underline{a}$$

Retirees die with probability $1-\nu$; hence, the effective discount factor is $\nu\beta$. Agents leave no bequests and, thus, the payoff in case of death is zero. $\delta \in [0,1]$ is the depreciation rate of physical capital and $r-\delta$ is the net return on asset holdings. Retired individuals do not participate in the labor market and, hence, they do not face employment or productivity risk.

Optimization Problem of the Working-Age Individual

A working-age individual with assets a, human capital h, labor market state s, and productivity z, chooses consumption and next period's assets to solve:

$$\begin{aligned} W^W(a,h,s,z) = \max_{a'} \Big\{ u(c) \quad & +\beta\theta \sum_{s'} \sum_{z'} \widehat{p}_h(s'|s)\pi_h(z'|z) W^W(a',h,s',z') \\ & +\beta(1-\theta) W^R(a',h) \Big\} \end{aligned} \tag{2.3}$$

subject to

$$c + a' = (1+r-\delta)a + y \qquad \text{and} \qquad a' \geq \underline{a}$$

With probability $1-\theta$, working age individuals retire and obtain the value of retirement, W^R, next period. An individual expects to move from its current labor market state s to s' with the subjective probability $\widehat{p}_h(s'|s)$. Crucially, we allow $\widehat{p}_h(s'|s)$, to differ from the actual probability, $p_h(s'|s)$. As before, in the context of the toy model, we refer to the difference between the subjective and the actual probability, $\Delta = \widehat{p}_h(s'|s) - p_h(s'|s)$, as the bias in individuals' expectations. The case $\Delta > 0$ reflects an optimistic bias and $\Delta < 0$ a pessimistic bias, and $\Delta = 0$ corresponds to rational expectations.

Lastly, individual labor productivity, z, can change as captured by $\pi_h(z'|z)$. Furthermore, guided by the findings of our empirical analysis we assume $\widehat{p}_h$ to be constant over time. In other words, we do not allow for changes in individual labor market expectations, for example, due to learning.

Labor earnings, y, depend on the individual's labor market state as follows:

$$y = \begin{cases} (1-\tau-\tau_{ss}) \cdot w \cdot z \cdot h & \text{employed} \\ (1-\tau) \cdot b(z,h) & \text{unemployed} \\ T & \text{not in the labor force} \end{cases}$$

When employed, a worker with human capital h and productivity z earns $z \cdot h \cdot w$, where w is the wage per efficiency unit of labor and $z \cdot h$ is the worker's labor supply in efficiency units. Labor earnings are subject to a proportional labor income tax τ and a social security tax τ_{ss}. Unemployed workers receive benefits $b(z,h)$ which are taxed at rate τ but exempt from social security taxes. We follow KMP and assume that benefits are a constant fraction ρ^u of the individual's potential wage, that is $b(z,h) = \rho^u z \cdot h \cdot w$. Furthermore, individuals who are not in the labor force receive welfare transfers, denoted by T. We model T as a constant fraction $\rho^n \in [0,1]$ of average labor earnings per worker in the economy.[16] T is an unconditional transfer and does not depend on worker's characteristics, hence, all individuals who are not in the labor force receive the same welfare benefits.

As usual, we impose that individuals take factor prices (w,r) and taxes (τ, τ_{ss}) as given when they optimize. Lastly, we assume about the timing of events at birth that a newborn individual first draws its human capital level according to $P(h)$, and conditional on the realization of h, she draws the labor market state according to $P_h(s)$ and the initial labor productivity level according to $\Pi_h(z)$.

Government Policy

Government policy in our model economy consists of three parts: unemployment insurance, welfare transfers and social security. Unemployment benefits and welfare transfers are financed by the revenues accruing from the labor income tax τ. We assume government budget balance which requires the following condition to hold:

$$\begin{aligned} \tau \textstyle\sum_h \sum_z P_h \Pi_h(z) \Bigg[P_h(e) wzh + P_h(u) b(z,h) \Bigg] = & \underbrace{\sum_h \sum_z P_h P_h(u) \Pi_h(z) b(z,h)}_{\text{Unemployment benefits}} \\ & + \underbrace{\sum_h \sum_z P_h P_h(n) \Pi_h(z) T}_{\text{Welfare benefits}} \end{aligned} \tag{2.4}$$

[16] Average labor earnings are computed as $w \frac{\sum_h P_h P_h(e) \sum_z \Pi_h(z) zh}{(\sum_h P_h P_h(e))}$, which is the wage per efficiency unit of labor times the efficiency labor per employed worker.

We use the definitions of $b(z,h)$ and T and rewrite this expression to obtain the budget balancing tax rate

$$\tau = \frac{\sum_h \sum_z P_h \Pi_h(z)\Big(P_h(u)\rho^u zh + P_h(n)\rho^n z\bar{h}\Big)}{\sum_h \sum_z P_h \Pi_h(z) zh\Big(P_h(e) + P_h(u)\rho^u\Big)},$$

which is equal to total benefits (for UI and welfare) divided by total before-tax labor income (worker's earnings and unemployment income).

The social security program is run as a balanced budget PAYGO system. Pension benefits are financed by the receipts of the payroll tax τ_{ss} which is levied on the labor earnings of employed workers. Hence, the budget constraint of the social security program is:

$$\Pi_R \sum_h P_h b_{ss}(h) = \tau_{ss}\Pi_W \sum_h P_h P_h(e) wh \sum_z \Pi_h(z) z \tag{2.5}$$

Using the definition of $b_{ss}(h)$, we can express the social security tax rate as:

$$\tau_{ss} = \rho_{ss} \cdot \frac{\Pi_R}{\Pi_W} \cdot \frac{\sum_h \sum_z P_h h \Pi_h(z) z}{\sum_h \sum_z P_h P_h(e) h \Pi_h(z) z}$$

Recursive Competitive Equilibrium

The state space of the economy is described by a time-invariant cross-sectional distribution, Φ, of individuals across age $j \in \{W, R\}$, labor market status $s \in \{e, u, n\}$, labor productivity $z \in Z$, human capital $h \in \{h_L, h_M, h_H\}$ and assets $a \in A$.

Definition 1. *The recursive competitive equilibrium in the model economy is defined as a collection of value functions (W^W, W^R), policy functions (c, a'), factor prices (r, w), and taxes (τ, τ_{ss}) such that*

- *given factor prices and taxes, the value functions are the solution to the individuals' optimization problem stated in Equations (2.2) and (2.3) and (c, a') are the optimal policy functions for consumption and next period's assets.*
- *the factor prices satisfy the firm's optimality conditions stated in (2.1)*
- *the government budget constraints in (2.4) and (2.5) are satisfied*
- *markets clear*

$$N = \Pi_W \sum_h P_h P_h(e) \sum_z \Pi_h(z) hz$$

$$K = \int a d\Phi$$

Lastly, it is important to mention that we assume a veil of ignorance to exist implying that individuals have an incomplete model of the macroeconomy. That is, they do not know the equilibrium mapping between primitives and the aggregate state. If individuals knew the expectations of all others, they could infer that there is a discrepancy between the actual and the subjective probability distribution because the aggregate variables are not consistent with how the individuals perceive the economy.

4 Quantitative Analysis

4.1 Calibration

Next, we calibrate the full model to quarterly U.S. data. All calibrated values are reported in Table 2.5. The probability of retiring $1-\theta = \frac{1}{160}$ and the probability of dying $1-\nu = \frac{1}{60}$ are set so that individuals can expect 40 years of work life and 15 years in retirement. The probability that an individual is born with human capital h is given by P_h. Since, death and retirement are random and independent of h, the probability P_h is equal to the population share of working-age individuals with human capital h. We exploit this feature and calibrate P_h to match the observed share of low-skilled, medium-skilled or high-skilled individuals in the working-age population. We define low-skilled individuals as those who have at least a high school degree, middle-skilled as those with a high school degree, but no college degree, and high-skilled as those with at least a college degree. To compute the population shares, we use the data from the 2014-2019 American Community Survey (ACS) and we restrict the sample to individuals aged between 25-60 years.[17]

The quarterly depreciation rate of physical capital δ is set equal to 2.5%. As is standard, we set $\alpha = 0.36$ which implies a capital share of 36%. We calibrate the personal discount factor to match a 4% annual net return to capital. The implied value of β is 0.9878. In the baseline calibration we set the borrowing limit $\underline{a}$ equal to zero, and the coefficient of relative risk aversion σ to unity, which implies log-utility.

Government policy in our model economy is parameterized by the three replacement rates $\rho_u, \rho_{ss}, \rho_n$. We follow KMP and set the replacement rate for retirement benefits, ρ_{ss}, to 0.40 and the replacement rate for unemployment benefits ρ^u to 0.5. We calibrate the replacement rate for welfare benefits ρ^n to match the ratio of average income of welfare recipients to average labor earnings in the U.S. economy. We compute this ratio from the 2015-2019 waves of the March supplement of the Current Population Survey. Welfare income includes income from public assistance, survivor's and disability benefits, worker's compensation (due to job-related injury or illness), educational assistance, or child support. We define the sample of welfare recipients as non-retired individuals who did not work and were not looking for work and who

[17] ACS data are extracted from the IPUMS data repository; see Ruggles et al. (2021).

reported to have received no labor earnings or retirement income. The details of the calculation are in Appendix H.1.

To calibrate $p_h(s'|s)$ and $\widehat{p}_h(s'|s)$ for all three skill groups, we use the values on the actual and the subjective labor market transition probabilities from Section 2, and we adjust these probabilities to fit the quarterly calibration.[18]

Next, we calibrate the Markov process that governs the evolution of idiosyncratic labor productivity. This involves finding values for the levels of labor productivity z and the transition probabilities $\pi_h(z'|z)$. It is important to notice that idiosyncratic labor productivity, z, is the only source of changes in individual labor earnings –given by $w \cdot z \cdot h$– because worker's human capital h and the wage per efficiency unit w are both constant in equilibrium. Following much of the related literature, we exploit this feature and use data on individual labor earnings to calibrate the process of z. In particular, we follow KMP and assume that individual labor earnings follow a continuous stochastic process with a transitory and a persistent component:

$$\log(z_t) = p_t + \epsilon_t, \qquad \text{where} \qquad p_t = \phi_h p_{t-1} + \eta_t.$$

Here, ϕ governs the persistence of the process. ϵ_t and η_t are the innovations of the persistent and the transitory shocks, respectively, with variances $\sigma^2_{\epsilon,h}$ and $\sigma^2_{\eta,h}$. Importantly, we allow the stochastic income process to be different across human capital types. Consequently, the parameters governing the process are indexed by h. We estimate the parameters $(\phi_h, \sigma^2_{\epsilon,h}, \sigma^2_{\eta,h})$, with data on annual individual labor earnings from the Panel Study of Income Dynamics (PSID). See Appendix I for the details of the estimation procedure. Table 2.5 contains the estimated parameters.

Overall, we find that the estimated income processes are very similar for different education groups. The persistent parameters, ϕ_h, are not statistically different from each other and, if anything, the variance of the transitory and the persistent component, $\sigma^2_{\epsilon,h}$ and $\sigma^2_{\eta,h}$ slightly increase with education. The parameter estimates in the table are at an annual frequency. To make the estimates consistent with the quarterly calibration, we convert the values to quarterly frequency by calculating $\phi_h = \hat{\phi}_h^{\frac{1}{4}}$ as well as $\frac{\sigma^2_\eta}{1-\phi^2} = \frac{\hat{\sigma}^2_\eta}{1-\hat{\phi}^2}$. Next, we use our estimates to approximate the continuous stochastic process for z with a discrete Markov chain with 21 states. More concretely, we approximate the persistent component of the process by a discrete seven-state Markov chain using the Rouwenhorst method (see Kopecky and Suen (2010)) and we discretize the transitory component using the Tauchen method (Tauchen (1986)) with three grid points.

Lastly, we calibrate the deterministic part of individual labor productivity h. We normalize the value of h for the lowest education group to $h_L = 1$. Since the wage w is

[18] The details of the adjustment procedure are in Appendix H.2.

Explanation	Parameter	Value			Source/Target
Life cycle					
Probability of retiring	$1-\theta$	0.0063			40 years of work life
Probability of dying	$1-\nu$	0.0167			15 years in retirement
Technology					
Depreciation rate	δ	2.5%			
$Y = K^{\alpha}N^{1-\alpha}$	α	0.36			Capital share of 36%
Preferences					
Personal discount factor	β	0.9878			4% annual net return
Coefficient of RRA	σ	1			log utility
Borrowing limit	$\underline{a}$	0			No borrowing
Government policy - replacement rates					
Retirement benefits	ρ_{ss}	0.40			KMP
Unemployment benefits	ρ^{U}	0.50			KMP
Welfare benefits	ρ^{n}	0.022			CPS
Human capital specific parameters		L	M	H	
Probability of being born with h	P_h	0.37	0.30	0.33	ACS
Persistence of labor productivity	ϕ	0.9677	0.9614	0.9661	PSID
Variance of persistent component	σ_{η}^2	0.0126	0.0135	0.0147	PSID
Variance of transitory component	σ_{ϵ}^2	0.0640	0.0767	0.0847	PSID
Deterministic productivity level	h	1.00	1.29	1.76	PSID

L: Low-skill, M: Medium-skill, H: High-skill.

Table 2.5: Calibrated parameter values

the same across skill groups, h_M and h_H determine the education premium of earnings of medium-skilled workers and high-skilled workers, respectively. We exploit this feature to calibrate h_M and h_H. More concretely, we use data from the 1968-2019 waves of the PSID to estimate a Mincer regression of log hourly earnings on age controls, education dummies and year fixed effects. For consistency, we apply the same sample selection criteria as before and apply our previous definition of education groups. In the regression, we use the low-skilled as reference group. The estimated coefficients on the education dummies imply values of $h_M = 1.29$ and $h_H = 1.76$.

4.2 Results

First, we report the quantitative properties of the equilibrium in terms of individual and aggregate outcomes.[19] Whenever possible, we compare the model outcome with the counterpart in the data to gauge the empirical fit of the model. Our calibration implies an equilibrium quarterly net interest rate of $r - \delta = 1.02\%$, as well as unit wage equal to $w = 2.37$. The tax rates that balance the government budget constraints

[19]The equilibrium of the model is solved numerically. See Appendix J for the details of the numerical algorithm.

	Wealth share		s/y
	Data	Model	Model
Q1	-0.9	0.2	4.1
Q2	0.8	1.5	7.3
Q3	4.4	5.1	13.1
Q4	13.0	15.3	20.8
Q5	82.7	77.9	34.3
90-95	13.7	17.5	
95-99	22.8	26.3	
Top 1%	30.9	15.1	
Gini	0.77	0.74	

Wealth share: Share of each quintile, or percentile in total wealth.
s/y: Average savings rate, in %

Table 2.6: Wealth inequality – model and data

(2.4) and (2.5) are equal to $\tau = 2.3\%$ and $\tau_{ss} = 19.7\%$. Moreover, we obtain a quarterly capital to output ratio of $K/Y = 10.2$ and an investment to output ratio of $I/Y = 0.26$. These values are in line with those typically applied in the RBC/DSGE literature. For example, Cooley and Prescott (1995) obtain values of $K/Y = 9.76$ and $I/Y = 0.252$.

In our calibration, we use the empirical labor market transition probabilities, $p_h(s'|s)$. Hence, not surprisingly, the model matches the observed 2014-2019 average employment-to-population ratio as well as the unemployment rate for each education group. Table 2.6 shows that the wealth distribution implied by the model matches very well the high degree of wealth inequality in the U.S. economy.[20] In particular, the model can account for the empirical feature that individuals in the first two quintiles essentially hold no significant amount of wealth and that most of the wealth is concentrated in the top quintile. The implied Gini coefficient of 0.74 is very close to that of the U.S. economy of 0.77. The model's success to account for the observed inequality in wealth is based on its ability to generate a realistic saving behavior across wealth quintiles. As shown by Dynan et al. (2004) there exists a strong positive association between wealth and saving rates in U.S. data. Our model can reproduce this pattern as shown in the column labeled s/y in Table 2.6.

In the model, we distinguish between three education groups: low-, medium-, and high-skilled individuals. According to our calibration, these groups differ in terms of various dimensions that matter for individual asset accumulation. This includes, for example, the value of the deterministic component of labor productivity h, and the

[20] The empirical wealth distribution is taken from Krueger et al. (2016) who compute the distribution from PSID data.

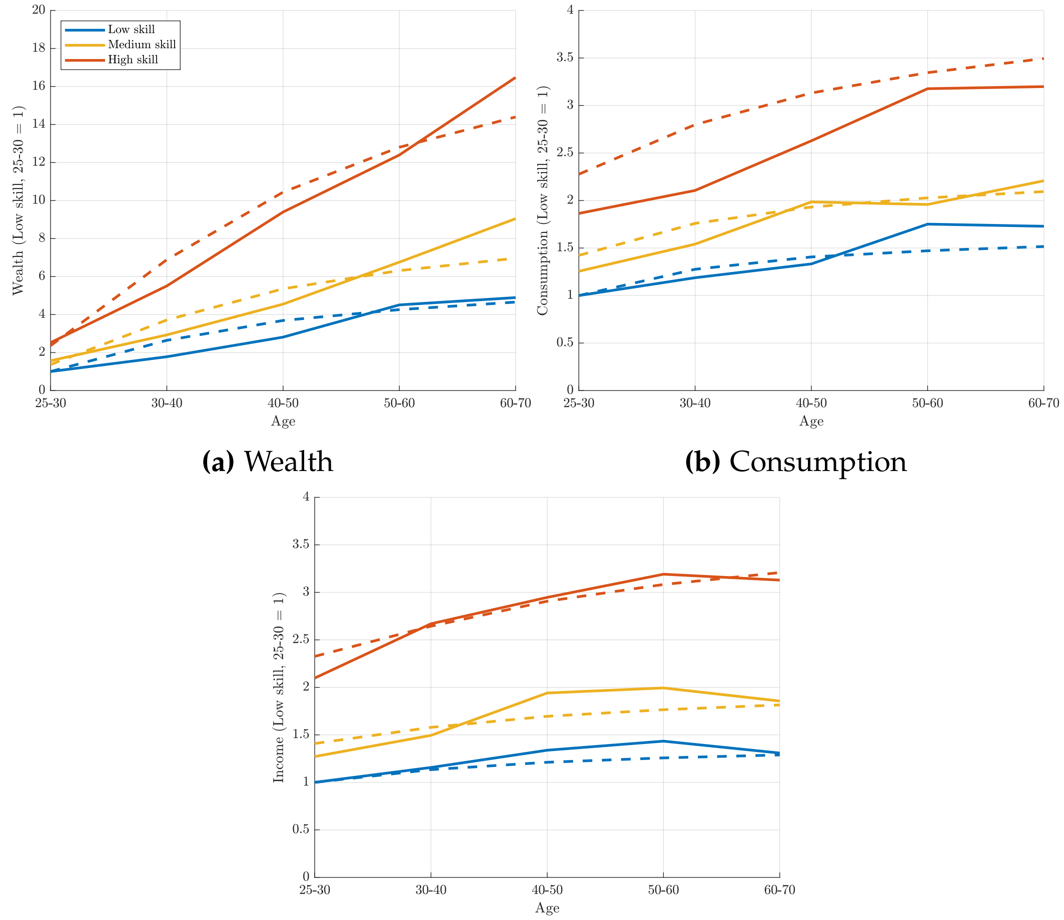
	Data			Model		
	L	M	H	L	M	H
Share in wealth, total	0.18	0.18	0.64	0.20	0.25	0.55
Share in wealth, 1^{st} quintile	0.53	0.25	0.22	0.46	0.29	0.25
Share in wealth, 5^{th} quintile	0.14	0.16	0.69	0.16	0.23	0.61

L: Low-skill, *M*: Medium-skill, *H*: High-skill.

Table 2.7: Share of wealth by education group – model and data

process of the stochastic component of labor productivity z. As a result, the wealth holdings differ, on average, across education groups. Table 2.7 reports the share of wealth held by each education group. The first row shows that more than half of aggregate wealth is held by high-skilled individuals whereas the low-skilled account for only about one fifth. This pattern is quite different across the quintiles of the wealth distribution. In the first quintile, the largest share is held by the low-skilled (second row) whereas the asset rich individuals are predominately high-skilled (third row). To compute the empirical analogue of these statistics, we use data from the 2017-wave of the PSID on individual net worth. Table 2.7 shows that overall, the model can replicate the pattern in the data remarkably well, even though in our calibration we did not target any data moments related to aggregate inequality or asset holdings by education group.

Next, we explore the model fit in terms of outcomes at the individual level. In particular, we focus on the life cycle pattern of individual (pre-tax) income, asset holdings and consumption. The individual life cycle in the model consists of two parts: working-age and retirement. To compute individual life cycle patterns, we simulate the equilibrium of the model over a long time horizon and for a large number of individuals. In this simulation, we keep track of each individual's age, as well as her income, assets and consumption in each period of its life cycle. This procedure allows us to compute individual life cycle statistics that we can compare to the data. To compute the data counterparts, we use information on individual income, consumption expenditures and net worth from the 2017-wave of the PSID. Figure 2.1 shows the results for the five age groups $[25-30)$, $[30,40)$, $[40,50)$, $[50,60)$, $[60,70)$. Newborn individuals in the model correspond to age 25 in the data. In each of the panels, we normalize the series by the value for the low-skilled individuals belonging to age group $[25-30)$. Generally, the model (dashed line) can match very well the observed life cycle profiles of individual income, asset holdings and consumption for the different education groups. Again, this is not evident, as our calibration did not target any data moment related to individual life cycle outcomes. In particular, the model can



(a) Wealth

(b) Consumption

(c) Income

Figure 2.1: Lifecycle path of income, wealth and consumption; Model (dashed) and Data (solid)

account for the very large –almost 8-fold increase– in asset holdings for high-skilled individuals and the comparatively modest increase for the low-skilled. Individual consumption rises much less than asset holdings over the life cycle, which is implied by the consumption-smoothing motive. By and large, the increase in individual consumption is similar across education groups but, of course, there are important differences in the level –both in the model and in the data. Lastly, the model also gets very close in matching the slope and the level differences across education groups in the empirical life cycle path of individual income.

According to our calibration, individuals tend to over-estimate the probability of favorable labor market events (such as remaining or becoming employed) and under-estimate the probability of adverse events (leaving or remaining out of the labor force). As a result, individuals systematically over-predict their future income. For example, an unemployed individual expects to become employed and to earn labor income next period with a probability that is higher than the actual probability. Since labor earnings are generally higher than unemployment benefits, the individual over-predicts

	All	L	M	H
$\widehat{E}(y') - E(y')$	1.80	2.54	1.58	1.19
$\widehat{E}(c') - E(c')$	0.69	1.05	0.59	0.39

In percent of actual future income.
L: Low-skill, M: Medium-skill, H: High-skill.

Table 2.8: Bias in expected income and consumption (model)

its next period's income. The same logic also applies to next period's consumption. In the absence of complete markets, the level of consumption in each period depends on the individual's period income. As a consequence of higher expected income, individuals also over-predict their future consumption. Table 2.8 shows by how much individuals over-predict their next-period's income and consumption. The findings in the table imply that, on average, individuals' expected future income is 1.80% higher than their actual future income. As before, the low-skilled are more over-optimistic which is reflected by their higher forecast error with respect to future labor income and consumption.

It is of interest to explore the extent to which these model predictions are confirmed by data. Unfortunately, the exact empirical counterparts of the model variables are not available in the SCE. Nevertheless, we resort to data outcomes which are arguably closely related in order to gauge the empirical validity of the model predictions –at least qualitatively. Concretely, we use information on individual's expected earnings, household income and consumption expenditure growth from the SCE and compute a 4-months growth rate of these measures. Moreover, we use the information from the SCE on individuals' expected inflation to obtain the growth rate of real variables.[21] The results of these calculations are in Table 2.9 in the rows labeled "Expected". We report the expected growth rates for the full sample and separately by skill group and labor market status. In order to assess the expectation bias, the table also shows the realized growth rates of the respective variables ("Actual"). We compute these growth rates using panel data from the PSID on individual earnings, household income and expenditures. For consistency, we deflate all nominal variables to express growth in real terms.

Clearly, there are conceptual differences between the measures of labor income and consumption expenditures in the model and the data-outcomes reported in the table. For example, in the model, the expectation of employed individuals concerning future labor income includes their perception of idiosyncratic productivity changes, as well as the effect on earnings of potential intermittent periods of non-employment. In

[21] In Appendix K we describe the calculation of expected and actual growth of individual income, earnings, and expenditures.

		by skill			by state	
	All	L	M	H	E	(U, N)
Earnings (real, 4-months growth, in %)						
Actual	0.67	0.36	0.70	0.89		
Expected	1.39	1.40	1.16	1.51		
Income (real, annual growth, in %)						
Actual	1.15	0.03	1.36	2.05	1.36	-0.81
Expected	1.55	1.30	1.46	1.95	1.80	1.36
Expenditures (real, annual growth, in %)						
Actual	0.05	-0.10	-0.36	0.39	0.13	-0.65
Expected	0.89	0.95	0.85	0.90	0.94	0.90

L: Low-skill, M: Medium-skill, H: High-skill.

Table 2.9: Bias in expected earnings, income and expenditures (data)

the data, individuals' earnings expectations may be based also on additional factors which are not present in the model, for example their expectations of future changes in hours worked. Moreover, income and expenditures in the model are measured at the individual level whereas in Table 2.9 these variables are measured at the household level. A discrepancy may arise because in the data the expectation about future household income (or expenditures) may reflect not only how individuals perceive their own future income but also that of other household members. These conceptual differences should be kept in mind in the following comparison.

For all three variables displayed in Table 2.9 we find a substantial positive expectation bias. That is, individuals' expected growth of earnings, income and consumption expenditures consistently exceeds the realized growth. As such, these findings are in line with the model's prediction of over-optimism concerning future income and consumption expenditures. Moreover, according to the results, the expectation bias differs substantially across skill groups and it is largest for the low-skilled, whereas high-skilled individuals tend to have more accurate expectations. For example, low-skilled individuals expect real income to grow at 1.3% p.a., whereas realized growth is only 0.03% p.a. This difference amounts to a substantial positive expectation bias of 1.27%. Instead for middle- and high-skilled individuals, the difference between expected and actual income growth is substantially smaller and equal to 0.10% (in absolute value). This pattern is consistent with the predictions of our quantitative analysis that low-skilled individuals are strongly over-optimistic about favorable labor market transitions and, hence, they tend to over-estimate future income and consumption. In contrast, the high-skilled have more precise labor market expectations and, as a result, they have a smaller expectation bias about income and consumption. Lastly, it

by state			by skill		
	Baseline	$\widehat{p} = p$		Baseline	$\widehat{p} = p$
E	37.3	40.1	L	28.0	36.1
U	19.3	29.3	M	29.7	33.6
N	-55.5	-45.2	H	33.6	33.6

E: Employed, U: Unemployed, N: Not in labor force.
L: Low-skill, M: Medium-skill, H: High-skill.

Table 2.10: Saving rate with and without expectation bias

is worthwhile to notice that the optimistic bias in the data is particularly pronounced for jobless individuals. This is qualitatively consistent with the model because there unemployed individuals and non-participants overestimate the probability of finding employment or to enter the labor force. Both transitions are associated with an increase in income. Thus, the over-optimism regarding the favorable labor market transition translates into an optimistic bias regarding future income and consumption.

4.3 Eliminating the Expectation Bias

Given the focus of the paper, we are primarily interested in exploring how the bias in labor market expectations affects individual and macroeconomic outcomes. To address this question, we run the experiment in which we eliminate the bias altogether and assume that all individuals know the correct labor market transition probabilities. That is, we set $\widehat{p}_h(s'|s) = p_h(s'|s)$ for every h. All other model parameters are as before.

When agents have correct beliefs, they assign higher probabilities to the transition into bad states and they expect good states to realize with a lower probability than in the baseline case. As Table 2.10 shows, over-optimism in the subjective probabilities implies that agents save more and build up more asset holdings than in the baseline case. This is in line with the toy model in Section 3.1. The left-hand panel in Table 2.10 shows the average savings rates conditional on the labor market state. Employed agents and especially job seekers save more in the counterfactual economy than in the baseline economy. Moreover, when out of the labor force agents run down their assets less quickly because they expect to remain longer in this state than in the baseline case. The right-hand panel in Table 2.10 reports the savings rate by skill level. Since low-skilled individuals are relatively more over-optimistic in the baseline case than medium- and high-skilled, they experience the largest change in their expectations and, thus, they increase their savings rates by more than the other skill groups. As a consequence, asset holdings increase for all education groups but more so for the

Age		$[25-30)$	$[30-40)$	$[40-50)$	$[50-60)$	At retirement
	L	46%	49%	49%	48%	49%
Δ Assets	M	34%	31%	26%	22%	23%
	H	21%	14%	6%	1%	1%

L: Low-skill, M: Medium-skill, H: High-skill.

Table 2.11: Change in asset holdings (in %) after elimination of expectation bias

low-skilled. This is shown in Table 2.11 which reports the change in the life cycle path of asset holdings with respect to the baseline economy. For example, for the age group $[30-40)$ years the asset holdings of the low-skilled increase, on average, by 49% whereas that of the high-skilled increase by 14%.

As low-skill individuals are primarily concentrated at the lower end of the wealth distribution (see Table 2.7), the relatively larger increase of their asset holdings implies that wealth is distributed more equally and aggregate wealth inequality is lower than in the baseline economy.[22] Table 2.12 shows that the Gini coefficient of 0.67 in the economy without the bias in expectations is substantially lower than that in the baseline economy. This result has two important implications. First, the finding suggests that a substantial part of the inequality in U.S. wealth holdings is due to individuals having biased labor market expectations. Second, the bias in expectations is a key feature that allows the quantitative model to match the observed inequality in the data. In contrast, the version of the model with rational expectations fails to generate the high wealth concentration at the top.[23]

4.4 Welfare Effects of Biased Expectations

Next, we evaluate the welfare effects of the bias in subjective expectations. First, we address the question whether the optimist agents in our baseline economy would be better off being a realists. That is, we compute the equivalent variation in expected lifetime consumption that would make a new-born agent as well off in the baseline economy than in the counterfactual economy. However, it is important to notice that

[22]More asset accumulation implies a higher equilibrium capital stock in the counterfactual economy. The K/Y ratio increases from 10.2 in the baseline to 10.9. Since aggregate labor is unchanged, the equilibrium quarterly net interest rate drops from $r-\delta = 1.02\%$ to 0.81% and the unit wage rises from $w = 2.37$ to 2.45. The change in the factor prices adds to decline in aggregate inequality. Labor earnings are the primary source of income for asset poor individuals and, hence, they gain from the increase in the wage rate. In contrast, asset income plays an important role for the rich and thus, they loose from the lower interest rate.

[23]To allow for a fair comparison with the rational expectations approach, we also consider the case where we eliminate the expectation bias and recalibrate β (which is the only parameters calibrated internally). We obtain a similar result than before that the model with rational expectations cannot match the empirical wealth concentration.

	Data	Baseline	$\widehat{p} = p$
Q1	-0.9	0.2	0.7
Q2	0.8	1.5	3.2
Q3	4.4	5.1	7.9
Q4	13.0	15.3	18.3
Q5	82.7	77.9	69.9
90-95	13.7	17.5	16.1
95-99	22.8	26.3	22.6
Top 1%	30.9	15.1	12.3
Gini	0.77	0.74	0.67

Table 2.12: Wealth inequality with and without expectation bias

the welfare calculations are based on the equivalent variation that is computed from the actual expected lifetime consumption. That is, we calculate the expected value E_0 using the actual labor market transition probabilities $p_h(s'|s)$. Hence, the compensating variation expressed in this way describes the benefit from removing the expectation bias, which is structural in this model, from the viewpoint of the social planner. More concretely, we compute for a newborn agent with human capital h the value of ϕ that satisfies

$$\underbrace{E_0\left[\sum_t \beta^t u\big((1+\phi)c_{it}\big)\right]}_{\text{Economy w/ bias}} \quad = \quad \underbrace{E_0\left[\sum_t \beta^t u\big(\bar{c}_{it}\big)\right]}_{\text{Economy w/o bias}}$$

The first row in Table 2.13 shows that $\phi > 0$ for all education groups. That is, agents attain a higher level of welfare in the counterfactual economy. On average, the welfare gain is equal to 4.1%. This result is equivalent to that obtained in the context of the simple model in Section 3.1: without the bias in expectations agents have higher asset holdings and this allows them to sustain a higher path of lifetime consumption. To build up the higher level of assets, agents consume less in the initial phase of their life cycle and this has a negative effect in terms of utility. However, this negative effect is more than offset by the positive effect that results from higher levels of consumption in the later periods of life. As expected, the welfare gain is largest and equal to 5.4% for low-skill individuals who experience the largest adjustment in their savings behavior.

If instead of a social planner, we adopt the viewpoint of the agent in our model, then we should compute the expected value using the subjective labor market probabilities. In other words, we ask the agent in our model to report the value of ϕ that makes her indifferent between the baseline and the counterfactual economy. The results for this

	All	ϕ_L	ϕ_M	ϕ_H
E_0	0.041	0.054	0.038	0.028
$\widehat{E}_0$	-0.199	-0.281	-0.186	-0.110

First (second) row: the expected value, E_0 ($\widehat{E}_0$), is computed with the actual (subjective) transition probabilities p_h ($\hat{p}_h$).

Table 2.13: Consumption equivalent variation

case are in the second row of Table 2.13. Not unexpectedly, we obtain that $\phi < 0$ for all agents. The reason is simple: agents are over-optimistic in the baseline, hence, the counterfactual economy seems unattractive to them since there they face labor market transition probabilities which put more weight on the transitions into bad states.

In our model economy assets serve as a means of self insurance against adverse shocks. Hence, the stock of assets of an individual determines its ability to smooth consumption during bad states. Our previous findings imply that without the bias in expectations individuals have higher buffer stock savings, which generally leads to better self-insurance than in the baseline economy. To quantify the degree of individual consumption smoothing, we simulate the equilibrium of the model and we use the simulated data on individual income and consumption to estimate the following model

$$\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$$

Δc_{it} is the log-difference of individual i's consumption between periods t and $t-1$ and Δy_{it} is the log-difference of the individual's after-tax labor earnings. Of interest to us is the estimate of b which measures how changes in labor income translate into changes in consumption. Large values of b indicate a high dependence of period consumption on period income and thus reflect a low degree of consumption smoothing. We estimate the equation separately for each education group and show the results for b in Table 2.14.

All coefficient estimates reported in the table are statistically significant at the 1% level. The values indicate that both, in the baseline and in the counterfactual economy, less-skilled individuals are more exposed to income fluctuations and thus achieve a lower degree of smooth consumption. In the counterfactual economy without the bias in expectations, all agents hold more assets and, thus, they can better self-insure against bad shocks. This particularly applies to low skilled individuals who experience the largest drop in b and attain a level of consumption smoothing that is comparable to that of the high-skilled individuals.

Generally, according to our results, over-optimism induces agents to hold less private insurance against adverse labor market shocks than in an economy without bi-

	Baseline			$\widehat{p} = p$		
	L	M	H	L	M	H
b	0.133	0.095	0.075	0.077	0.071	0.069

Table 2.14: Consumption smoothing with and without expectation bias

ased expectations. This suggests that there is potentially room for welfare improving policies which counteract the lack of private insurance. However, arguably simply substituting public insurance for private insurance, for example by providing higher public benefits (for unemployment or retirement) would be ineffective as such measures would just crowd out private insurance. Likely more effective are incentives that improve private insurance via stimulating savings.

4.5 Robustness and Extensions

In this section we consider extensions to the baseline economy and modifications of the quantitative analysis in an effort to assess the robustness of our main findings. The results of the robustness checks are succinctly summarized in Table 12. Each column in the table corresponds to a specific robustness exercise. For comparability, we include in the column labeled "Benchmark" the outcomes of the baseline economy. The subcolumns "w" and "w/o" refer to the economy with and without expectation bias, respectively.

In the first step, we use in the quantitative analysis the subjective and the actual transition probabilities which are both computed from the same sample of individuals taken from the SCE. This is different from the baseline case where we compute the actual transition probability matrix from the CPS. As mentioned in Section 2 the SCE and the CPS generate qualitatively very similar patterns for the bias in expectations. There are, however, subtle differences in terms of magnitudes across the two datasets (see Table 2.19). For example, according to the results obtained from the SCE, job seekers underestimate the probability of dropping out of the labor force by 14.7 percentage points, which is 4 percentage points higher than the number computed from the CPS. Given these differences, we now want to assess whether the choice of the CPS instead of the SCE for computing the actual probabilities matters quantitatively through the lens of our model. Reassuringly, we can observe from the column labeled "*SCE*" in Table 2.15 that the properties of the equilibrium are very similar to the ones of the baseline case. Importantly, this includes the life cycle profile of individual consumption and asset accumulation and the aggregate wealth distribution. Moreover, when we eliminate the bias in subjective expectations we obtain very similar results compared to the same counterfactual exercise conducted in the baseline case. In view

	Benchmark		SCE		$\sigma = 2$		Labor		Bias for E, U, or N		
	w	w/o	w	w/o	w	w/o	w	w/o	E	U	N
Panel (a): Savings rate, in %											
L	28.0	36.1	26.5	37.3	28.9	38.8	29.7	35.6	32.7	34.9	32.6
M	29.7	33.6	30.9	34.3	30.1	36.1	30.3	33.3	32.1	32.4	32.7
H	33.6	33.6	33.6	31.1	34.0	35.9	34.4	34.3	32.9	33.7	34.5
Panel (b): Assets at retirement entry											
L	23.3	34.6	20.9	35.1	24.5	38.8	9.7	13.3	29.5	32.7	29.4
M	35.9	43.9	40.8	48.2	37.0	49.2	13.7	16.2	40.7	41.5	41.9
H	70.0	70.8	77.8	69.7	71.8	79.1	25.9	26.3	68.2	71.0	73.7
Panel (c): Consumption at retirement entry											
L	2.2	2.7	2.2	2.7	2.3	2.9	0.9	1.1	2.4	2.6	2.5
M	2.9	3.3	3.1	3.5	3.1	3.6	1.2	1.3	3.2	3.2	3.2
H	4.8	5.1	5.2	5.1	5.0	5.5	1.8	2.0	4.9	5.1	5.1
Panel (d): Labor supply, in %											
L							33.8	34.5			
M							32.5	33.0			
H							30.6	31.1			
Panel (e): Gini coefficient											
	0.74	0.67	0.74	0.68	0.71	0.64	0.75	0.68	0.70	0.68	0.69
Panel (f): Consumption smoothing											
b_{all}	0.10	0.07	0.10	0.09	0.09	0.07	0.06	0.04	0.09	0.08	0.07
Panel (g): Welfare, in %×100											
ϕ_L	5.37		5.95		12.1		5.29		3.77	4.89	4.35
ϕ_M	3.81		2.94		9.94		3.63		2.48	3.25	3.26
ϕ_H	2.80		1.62		7.74		2.55		1.40	2.35	2.36

SCE: Actual and subjective transition probabilities are computed from SCE;
σ= **2**: Coefficient of relative risk aversion is set equal to 2.0;
Labor: Model economy with endogenous labor supply;
Bias for E, U, or N: Only employed individuals (E), or unemployed individuals (U), or non-participants (N) have biased expectations
w (w/o): subjective expectations in the model are with (without) bias;
L, M, H: Low-, middle-, high-skilled.
Panel (a): Average savings rate of working-age individuals.
Panels (b,c): Average level of assets and consumption of new retirees.
Panel (d): Average labor supply by employed working-age individuals.
Panel (f): Coefficient estimate of b from $\Delta c_{it} = a + b \cdot \Delta y_{it} + e_{it}$.
Panel (g): Consumption equivalent variation required to make a new-born individual in the economy with the bias as well off as in the economy without the bias.

Table 2.15: Results of robustness analysis

of these findings, we conclude that the choice of the CPS, instead of the SCE, as a dataset for calculating the actual transition probabilities has no significant relevance for our main findings.

In the baseline, the coefficient of relative risk aversion, $\sigma = 1$, implies log-utility. Quite naturally, in the context of our model, agents' attitude towards risk arguably plays an important role. Thus we consider in the quantitative analysis the alternative value of $\sigma = 2$ to test the robustness of the baseline results with respect to the degree of the risk aversion. The results are reported in the column labeled "$\sigma = 2$" in Table 2.15. As can be observed from the table a higher value of risk aversion leads to more asset accumulation. This is in line with standard intuition. Interestingly, for a higher value of σ the elimination of the bias in expectation leads to a larger adjustment in individual savings than in the baseline and to a larger reduction in aggregate wealth inequality. Also the implied effect of expectation bias on welfare is higher because due to higher asset holdings, individuals in the counterfactual scenario are able to sustain a higher level of consumption.

Next, we extend the baseline economy to include an endogenous labor supply choice by employed individuals. The purpose of this extension is twofold. First, we want to study whether the observed bias in subjective labor market expectations per se has a sizable quantitative effect on individual labor supply. Second, we want to generally assess whether the baseline results of Section 4.2 are robust to allow for an endogenous labor choice. We assume additively separable preferences in consumption and leisure. As in the baseline economy, transitions between the labor market states are governed by the Markov process but, unlike before, employed individuals can optimally choose the amount of hours to work. See Appendix L for the full description of the framework and the calibration of the extended model. The results are reported in the column labeled "Labor" in Table 2.15. The pattern for individual labor supply shown in Panel (d) of the table are in line with basic intuition: over-optimism induces individuals to work less hours because they expect to stay employed for longer, and in case of job loss, they expect to be reemployed faster than it is actually the case. Generally, the low-skilled individuals hold little assets and thus, when the bias in subjective expectations is eliminated, they react more strongly and increase their hours by more than the high-skilled. This is particularly the case for younger individuals who hold little wealth. While the increase in hours worked for the low-skilled is, on average, relatively modest and equal to $34.5 - 33.8 = 0.7$ percentage points, it is much more pronounced and equal to 3.7 percentage points for the age group $25 - 30$ years. Importantly, as can be seen from the table the results obtained for our baseline economy are generally robust to the inclusion of an endogenous labor supply choice. If anything, the welfare effects are slightly lower which can be explained by the higher labor supply in the counterfactual economy that implies larger disutility of working.

Lastly, an important empirical finding of Section 2 was that employed and unemployed individuals, as well as non-participants, all have biased expectations about labor market transitions. Now, we want to understand whether the expectation bias of one of these three groups is quantitatively more important than that of the others for explaining the results. To this end, we re-run the quantitative analysis but allow only a given labor market group to have biased subjective expectations. The two other groups are assumed to have the correct expectations.[24] In the column labeled "Bias for E, U, or N" in Table 2.15 we report the properties of the implied equilibria when only the employed individuals (column *E*), or the unemployed individuals (*U*), or the non-participants (*N*) have a bias in their expectations. Clearly, the equilibrium values of these hypothetical scenarios lie in between the values of the baseline economy where all individuals have biased expectations (column "Baseline w") and the counterfactual economy where no group has a bias (column "Baseline w/o"). According to the findings in the table none of the three groups stands out particularly prominently but the bias of each groups is quantitatively important.

5 Conclusion

In this paper we use survey data from the U.S. Survey of Consumer Expectations to document household expectations about individual labor market transitions. We find evidence for a substantial optimistic bias in expectations. Households tend to overestimate the probability of experiencing a transition into a favorable labor market state (finding a job, remaining employed) and they underestimate the probability of transiting into a bad state (leaving the labor force). Furthermore, we document the heterogeneity in the bias across different demographic groups and we find a strongly negative relation between education and the degree of over-optimism. Individuals with a high-school degree (or less) tend to be strongly over-optimistic about their labor market prospects. In contrast, college educated individuals –who are still over-optimistic– have substantially more precise beliefs.

We explore the implications of biased labor market expectations on individual choices and aggregate outcomes; first, within a stylized two-period model, and second in the context of a calibrated quantitative life cycle model. We show that the optimistic bias generally discourages individual savings and thereby dampens wealth accumulation. The effect on life cycle consumption allocation is quantitatively sizable and implies a substantial loss in welfare of individuals compared to the allocation under full information. As a key result, we establish that the heterogeneity in the bias leads to pronounced differences in the accumulation of assets across individuals, and is thereby a quantitatively important driver of inequality in wealth.

Our results have important implications for economic policy. Generally, in the presence of positively biased expectations, agents hold less private insurance (in the form of wealth) than under full information, which impedes their ability to smooth con-

[24]We also consider the alternative approach, where we turn-off the bias for one group but keep it for the other two. This approach leads to very similar conclusions.

sumption over the life cycle and against income fluctuations. Providing (more) public insurance to compensate for the lack in private insurance would not be an adequate policy measure because of crowding out. An arguably more promising approach is to provide incentives to increase private insurance by stimulating savings and wealth accumulation. We consider the analysis of such policies a promising avenue for future research.

Appendices

A Descriptive Statistics and Calculation of Subjective and Actual Probabilities

A.1 Subjective Probabilities

We use the ”Labor Market Module” of the Survey of Consumer Expectations (SCE). This supplement is conducted every four months. The question of interest was first introduced into the survey in July 2014; thus, our dataset covers the period from July 2014 until November 2019, which is the date with the most recent available data (as of writing). We consider the sample of individuals aged 25 to 60 year, who report not to be enrolled in school or college. We define individuals as employed, if they report as their current employment status either ”Working full-time”, ”Working part-time”, or ”sick or other leave”. Unemployed individuals are those who report to be (i) ”temporarily laid off”, or (ii) ”not working, but would like to work” and who state that they have ”done something in the last 4 weeks to look for work”. Lastly, individuals are defined as non-participants if they report to be ”Permanently disabled or unable to work”, ”Retiree or early retiree”, ”Student, at school or in training”, or ”Homemaker”. In addition, we classify individuals as non-participants if they report that they would like to work but haven't searched for employment during the last 4 weeks. Note that the question about the past job search is only available every four months as part of the Labor Market Module. We exclude all observations for which we cannot determine the labor market status.

Table 2.16 reports the number of observations in the sample for different demographic groups and labor market states. The first two columns represent the subsample of individuals for which we have information about the individual actual labor transitions. Columns three and four represent the sample of individuals from which we compute the subjective expectations.

	SCE				CPS	
	Actual		Subjective		Actual	
	Obs	%-share	Obs	%-share	Obs	%-share
Men	3,044	49.27	6,044	48.52	1,821,125	49.04
Women	3,136	50.73	6,348	51.48	1,967,713	50.96
25–29	750	11.62	1,534	12.16	496,254	14.56
30–39	1,606	25.07	3,279	25.48	1,041,851	27.65
40–49	1,716	28.21	3,419	28.15	1,010,370	26.54
50–54	914	15.06	1,841	14.96	555,329	14.16
55–60	1,194	20.04	2,320	19.26	685,034	17.09
$\leq$HS	649	33.48	1,327	33.82	1,386,627	36.91
C	1,926	29.44	3,966	29.99	1,038,170	26.91
$\geq$Bachelor	3,605	37.07	7,096	36.18	1,364,041	36.18
White	5,046	80.63	10,104	80.72	3,035,009	76.92
Non-white	1,134	19.37	2,289	19.28	753,829	23.08
Single	2,085	34.10	4,175	33.85	1,512,200	40.78
Married	4,095	65.90	8,218	66.15	2,276,638	59.22
$<$30,000	947	22.91	1,905	22.51	753,842	20.05
30,000–49,000	946	16.52	1,928	17.17	660,401	17.57
50,000–99,000	2,243	31.74	4,461	31.81	1,264,007	32.84
$\geq$100,000	2,021	28.83	4,052	28.51	1,110,588	29.54
E	5,256	81.19	10,553	81.54	2,920,734	77.00
U	188	3.38	365	3.37	111,747	3.05
N	736	15.43	1,475	15.09	756,357	19.95

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019.
Obs: Number of observations. %-share: Population shares in sample using weights.

Table 2.16: Descriptive statistics for subjective and actual transition rates

A.2 Actual Probabilities

The actual transition probabilities are computed from CPS data on individual labor market transitions.The CPS is a monthly, nationally representative survey of around 60,000 households. It is conducted by the Bureau of Labor Statistics and its primary purpose is to evaluate the current state of the U.S. labor market. Every individual in the CPS is interviewed for 4 successive months and, after a break of 8 months, it is interviewed again for 4 months. This structure implies that we can directly observe 1–3 months as well as, 9–15 months labor market transition rates. To stay as close as possible to the SCE, we consider the same sample restrictions and period of time. That is, we consider individuals who are 25-60 years old, who are not enrolled in school or college, and who are not a member of the armed forces. We use waves from July 2014 to November 2019. The last two columns of Table 2.16 report the characteristics of the CPS-sample for different demographic groups. We compute the average m-month transition rate as the share of individuals who report to be in state s in one month and in state s' m months later. We use the CPS-survey weights to aggregate the individual observations. To obtain the 4-months transition probabilities, we interpolate linearly between the values for the 4-months, and the 9-months transition probabilities.

Both, the SCE and the CPS are designed to be nationally representative. However, Table 2.16 documents a number of differences in the composition of both samples. For example, the share of married individuals is higher in the SCE. This can be explained by the fact that respondents in the SCE are asked whether they are married or live together, whereas in the CPS the legal status of the respondent matters. Furthermore, individuals in the SCE are, on average, slightly older, better educated, and more likely to be employed than out of the labor force. The difference to the CPS could be due to the survey design of the SCE which requires respondents to have access to internet and to be able to fill out an online-questionnaire. A noteworthy feature of the SCE is that the labor market status is not considered in the construction of the sample weights. Consequently, there are notable differences between the SCE and the CPS in the joint distribution of age and education conditional on the labor market state. See Table 2.17 for an illustration of this discrepancy between the two datasets. To correct for these compositional differences, we use the CPS sample weights –listed in Table 2.17– to re-normalize the weights from the SCE for each education-age-labor cell.

The standard errors for the subjective transition probabilities –reported in Tables 2.1, 2.2, 2.20, 2.18, 2.22, 2.23, 2.24, 2.25, 2.19– are expressed as so-called linearized Taylor standard error and they are computed with the Stata command ”svy” (with ”pweights”). We use the same method to compute the standard errors for the actual 3-months and 9-month transition probabilities from the CPS. Then, we interpolate linearly between those two to obtain an approximation of the standard error for the 4-months transition probability.

		SCE			CPS		
		E	U	N	E	U	N
Age	Education						
25–29	≤HS	0.78	2.20	0.41	3.72	8.89	5.15
25–29	C	2.71	2.75	2.65	3.77	4.85	3.13
25–29	≥Bachelor	9.93	3.57	2.85	5.03	3.70	2.58
30–39	≤HS	2.15	4.40	2.85	8.23	14.57	11.25
30–39	C	6.92	6.59	6.45	7.54	8.65	6.10
30–39	≥Bachelor	18.86	13.46	7.12	12.21	6.42	6.23
40–49	≤HS	2.68	3.85	5.83	8.95	11.54	12.00
40–49	C	8.86	11.26	10.04	7.59	6.68	5.98
40–49	≥Bachelor	16.81	11.26	6.45	11.55	6.49	5.53
50–54	≤HS	1.77	1.37	3.05	5.23	6.18	8.88
50–54	C	5.53	8.24	8.01	4.22	3.80	4.00
50–54	≥Bachelor	7.47	6.59	4.14	5.60	3.73	2.95
55–60	≤HS	1.79	3.30	8.48	5.96	6.24	14.22
55–60	C	5.86	9.62	18.59	4.64	4.28	6.95
55–60	≥Bachelor	7.88	11.54	13.09	5.76	3.97	5.05
Total		100	100	100	100	100	100

Sample: Individuals with age 25-60 years, non-school or -college;
Period: 07/2014-11/2019.

Table 2.17: Sample composition conditional on labor market state

Panel (a): Baseline (CPS-weights)

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Panel (b): Survey-specific weights

	Subjective			Actual			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.16)	(0.10)	(0.10)	(0.03)	(0.02)	(0.02)	(0.16)	(0.10)	(0.10)
U	59.5	34.1	6.4	42.5	32.2	25.3	17.0	1.9	-18.9
	(2.10)	(1.81)	(1.10)	(0.31)	(0.30)	(0.28)	(2.12)	(1.83)	(1.14)
N	10.0	12.6	77.3	10.7	3.0	86.3	-0.7	9.6	-9.0
	(0.72)	(0.79)	(1.17)	(0.08)	(0.04)	(0.08)	(0.72)	(0.79)	(1.17)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Observations from the SCE and CPS are both aggregated using sample weights from the CPS. Panel (b): Observations from the SCE (CPS) are aggregated using sample weights from the SCE (CPS).

Table 2.18: 4-Months subjective and actual transition probabilities (with survey-specific weights)

Panel (a): Actual transition probabilities calculated from CPS

	Subjective			Actual (CPS)			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.4	95.2	1.5	3.3	0.9	1.0	-1.9
	(0.17)	(0.11)	(0.10)	(0.03)	(0.02)	(0.02)	(0.17)	(0.11)	(0.11)
U	61.3	32.1	6.6	42.5	32.2	25.3	18.8	-0.1	-18.7
	(2.24)	(1.83)	(1.22)	(0.31)	(0.30)	(0.28)	(2.27)	(1.85)	(1.25)
N	10.7	14.2	75.1	10.7	3.0	86.3	0.0	11.2	-11.2
	(0.80)	(1.04)	(1.40)	(0.08)	(0.04)	(0.08)	(0.80)	(1.04)	(1.41)

Panel (b): Actual transition probabilities calculated from SCE

	Subjective			Actual (SCE)			Subjective - Actual		
	E	U	N	E	U	N	E	U	N
E	96.1	2.5	1.5	96.7	1.8	1.6	-0.6	0.7	-0.1
	(0.23)	(0.14)	(0.15)	(0.38)	(0.27)	(0.28)	(0.44)	(0.30)	(0.32)
U	57.0	37.3	5.7	38.2	41.4	20.4	18.8	-4.1	-14.7
	(2.93)	(2.60)	(1.06)	(4.46)	(4.67)	(4.37)	(5.34)	(5.35)	(4.50)
N	10.5	12.2	77.3	6.8	2.6	90.6	3.7	9.6	-13.3
	(1.03)	(1.06)	(1.67)	(1.19)	(0.80)	(1.40)	(1.57)	(1.33)	(2.18)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Baseline case, actual transition probabilities computed from the CPS. Panel (b): Actual transition probabilities computed from the SCE.

Table 2.19: 4-Months subjective and actual transition probabilities.
(actual probabilities computed from CPS and SCE)

B Ability to Process Probabilities in SCE

The following three questions in the SCE ask the respondents to calculate and process probabilities

- **QNUM3**: *"In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize are 1%. What is your best guess about how many people would win a $10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?"*
- **QNUM5**: *"If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?"*
- **QNUM6**: *"The chance of getting a viral infection is 0.0005. Out of 10,000 people, about how many of them are expected to get infected?"*

The fraction of individuals in our sample who answer correctly is equal to: 83% for QNUM3, 89% for QNUM5, and 78% for QNUM6. We want to explore whether the bias in subjective expectations is significantly different for those individuals who are less able to deal with probabilities. To this end, we first split the sample into two groups: one group is composed of those individuals who gave an incorrect answer to at least one of the three control questions. The second group consists of the remaining 58% of individuals who answered all questions correctly. Then, we calculate the subjective probabilities for each group and compare them to the actual probabilities to assess the bias in expectations. For the actual probabilities we consider two cases. In the first case, we use –as in the baseline– the transition probabilities calculated from the CPS. In the second case, we account for the fact that the two groups of individuals could in principle differ in terms of the actual transition probabilities. Thus, we calculate the actual probabilities from the SCE. Hence, in this second case, the subjective and the actual probabilities for both groups are calculated from the same sample of individuals. Table 2.20 shows the results.

Actual probabilities calculated from CPS

	Subjective			Actual (CPS)			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
Panel (a): Wrong answer to at least one control question									
E	94.8	3.2	2.1	95.2	1.5	3.3	-0.4	1.7	-1.2
	(0.35)	(0.22)	(0.20)	(0.03)	(0.02)	(0.02)	(0.35)	(0.22)	(0.20)
U	60.0	31.5	8.5	42.5	32.2	25.3	17.5	-0.7	-16.8
	(3.35)	(2.64)	(1.88)	(0.31)	(0.30)	(0.28)	(3.36)	(2.66)	(1.90)
N	11.5	16.4	72.1	10.7	3.0	86.3	0.8	13.4	-14.2
	(1.17)	(1.59)	(2.09)	(0.08)	(0.04)	(0.08)	(1.17)	(1.59)	(2.09)
Panel (b): All control questions answered correctly									
E	97.0	2.0	1.0	95.2	1.5	3.3	1.8	0.5	-2.3
	(0.15)	(0.10)	(0.10)	(0.03)	(0.02)	(0.02)	(0.15)	(0.10)	(0.10)
U	63.5	32.9	3.6	42.2	32.8	25.0	21.3	0.1	-21.4
	(2.43)	(2.23)	(0.85)	(0.31)	(0.30)	(0.28)	(2.45)	(2.25)	(0.89)
N	9.4	11.1	79.4	10.6	3.0	86.4	-1.2	8.1	-7.0
	(1.01)	(1.07)	(1.64)	(0.08)	(0.04)	(0.08)	(1.01)	(1.07)	(1.64)

Actual probabilities calculated from SCE

	Subjective			Actual (SCE)			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
Panel (c): Wrong answer to at least one control question									
E	94.4	3.3	2.3	95.2	2.6	2.2	-0.8	0.7	0.1
	(0.51)	(0.31)	(0.30)	(0.76)	(0.55)	(0.54)	(0.91)	(0.63)	(0.61)
U	54.4	38.5	7.0	33.7	45.1	21.2	20.7	-6.6	-14.1
	(4.35)	(3.86)	(1.58)	(5.97)	(6.56)	(5.87)	(7.39)	(7.61)	(6.08)
N	11.9	14.6	73.5	7.2	3.7	89.1	4.7	10.9	-15.6
	(1.51)	(1.64)	(2.49)	(1.80)	(1.35)	(2.18)	(2.35)	(2.13)	(3.31)
Panel (d): All control questions answered correctly									
E	97.0	2.0	1.0	97.5	1.3	1.2	-0.5	0.7	-0.2
	(0.20)	(0.11)	(0.15)	(0.40)	(0.27)	(0.31)	(0.45)	(0.29)	(0.34)
U	61.2	35.2	3.6	45.5	35.5	19.0	15.7	-0.3	-15.5
	(3.13)	(2.89)	(0.88)	(6.40)	(5.91)	(6.43)	(7.12)	(6.58)	(6.49)
N	8.6	8.8	82.6	6.2	1.1	92.7	2.4	7.7	-10.1
	(1.32)	(1.06)	(1.94)	(1.40)	(0.40)	(1.46)	(1.92)	(1.14)	(2.42)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Panel (a): Baseline case. Panel (b): Subjective expectations of individuals who answered wrongly to at least one control question. Panel (c): Subjective expectations of individuals who answered correctly to all control questions.

Table 2.20: 4-months subjective and actual transition probabilities (control questions)

C Results from the Survey of Economic Expectations

The Survey of Economic Expectations (SEE) was conducted as national telephone survey by the University of Wisconsin Survey Center (UWSC) during the period from 1994-2002. The purpose of the SEE was to elicit probabilistic expectations of significant personal events. For example, respondents were asked to report expectations for crime victimization, health insurance, employment, and income. In addition, in some waves, respondents were asked about returns on mutual-fund investments and about their future Social Security benefits. See Dominitz and Manski (2020) for an introduction into the SEE. We consider the sample of individuals with 25-60 years of age. The survey question of interest to us asks employed respondent to report their expectations of future job loss. The specific survey question reads: *"I would like you to think about your employment prospects over the next 12 months. What do you think is the PERCENT CHANCE that you will lose your job during the next 12 months?"*. For the period 1994-2002, the average value of the subjective (12-months) probability of job loss is 14.6%.

As before, we measure the bias in expectations by comparing the subjective probabilities with the actual probabilities. As in the baseline, we use the CPS to compute the actual transition probabilities (the SEE does not have a panel dimension). According to our interpretation, the survey question in the SEE asks respondents about their expectation of an involuntary layoff and not a voluntary quit. Identifying involuntary layoffs in the CPS is challenging because individuals are not asked about the reason of the job separation. Thus, we use as an indicator whether and for how long individuals move into unemployment after a job separation. The underlying idea is as follows. First, workers who get fired move to unemployment rather than leave the labor force. This allows us to distinguish involuntary job separations from voluntary quits, which are followed by a transition out of the labor force. Second, the duration of the spell of unemployment after a separation likely depends on the reason of separation. Voluntary quits, which are induced by a job-to-job transition likely result in no, or only short spells of unemployment, while involuntary layoffs likely results in longer spells.

We use the Annual Social and Economic Supplement to the CPS (ASEC) for the period from 1994-2003 and we apply the same sample restrictions than in the SEE. The ASEC is conducted every 12 months. This allows us to calculate the actual probability of job loss for the same 12-months horizon, for which we calculate the subjective probability from the SEE. More concretely, we calculate the actual probability as the share of individuals who are employed in period t and who report to have experienced at least x weeks of unemployment in the period t and $t + 12$ months. We consider different values of $x \in \{1, 3, 5, 10\}$ to account for more or less stringent definitions of job loss. For the case of $x = 1$, the sample likely contains also observations of job-to-job

Probability of job loss (in %)										
		94-02	1994	1996	1997	1998	1999	2000	2001	2002
Actual (CPS)	$x = 1$	29.9	38.1	30.6	28.1	26.0	25.2	24.6	33.6	33.5
	$x = 3$	28.7	36.8	29.1	27.0	24.5	24.2	23.3	32.2	32.4
	$x = 5$	24.2	31.6	24.6	22.4	20.4	20.0	19.1	28.2	27.7
	$x = 10$	18.3	24.0	19.2	16.4	15.0	14.8	13.7	21.3	22.2
Subjective (SEE)		14.6	15.1	13.8	13.9	13.7	12.9	12.9	13.5	18.8
Sample: Individuals with age 25-60 years; Period: 1994-2002. Source: SEE and CPS.										

Table 2.21: 12-Months subjective and actual probability of job loss

transitions, whereas individuals who have experienced $x = 10$ weeks and more in unemployment are likely to be displaced workers. Table 2.21 reports the results for the subjective probability of job loss and the actual probability for the different cases.

D Expectation Bias for Different Demographic Groups

	Subjective			Actual			Subjective – Actual		
Education									
	E	U	N	E	U	N	E	U	N
High school or less									
E	95.28	2.87	1.85	93.46	2.16	4.38	1.82	0.71	-2.53
	(0.45)	(0.29)	(0.26)	(0.05)	(0.03)	(0.04)	(0.45)	(0.29)	(0.26)
U	61.35	29.03	9.61	39.63	31.85	28.52	21.72	-2.82	-18.90
	(4.23)	(3.25)	(2.41)	(0.45)	(0.43)	(0.42)	(4.26)	(3.27)	(2.44)
N	10.45	15.26	74.29	9.12	2.82	88.06	1.33	12.44	-13.77
	(1.39)	(1.88)	(2.51)	(0.10)	(0.06)	(0.11)	(1.40)	(1.88)	(2.51)
Some college									
E	95.91	2.40	1.69	95.07	1.62	3.31	0.85	0.77	-1.62
	(0.25)	(0.15)	(0.18)	(0.05)	(0.03)	(0.04)	(0.26)	(0.15)	(0.19)
U	63.80	32.62	3.59	42.38	32.49	25.13	21.41	0.13	-21.54
	(2.72)	(2.50)	(1.03)	(0.58)	(0.56)	(0.52)	(2.78)	(2.56)	(1.15)
N	10.77	13.82	75.41	11.05	3.38	85.57	-0.28	10.44	-10.16
	(0.90)	(1.01)	(1.47)	(0.15)	(0.09)	(0.17)	(0.92)	(1.01)	(1.48)
College or higher									
E	96.93	2.22	0.84	96.66	1.00	2.34	0.27	1.22	-1.49
	(0.13)	(0.09)	(0.08)	(0.03)	(0.02)	(0.03)	(0.13)	(0.09)	(0.09)
U	58.46	37.35	4.19	47.90	32.55	19.54	10.56	4.79	-15.35
	(2.60)	(2.45)	(0.87)	(0.63)	(0.60)	(0.50)	(2.67)	(2.52)	(1.01)
N	11.07	12.24	76.68	13.88	2.85	83.27	-2.81	9.39	-6.59
	(1.13)	(1.07)	(1.69)	(0.18)	(0.09)	(0.19)	(1.15)	(1.07)	(1.70)
Gender									
	Subjective			Actual			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
Male									
E	96.24	2.40	1.37	96.03	1.58	2.39	0.20	0.82	-1.02
	(0.23)	(0.13)	(0.15)	(0.03)	(0.02)	(0.03)	(0.23)	(0.13)	(0.15)
U	64.22	33.10	2.68	44.12	34.57	21.31	20.10	-1.47	-18.63
	(3.44)	(3.28)	(0.78)	(0.44)	(0.42)	(0.36)	(3.47)	(3.31)	(0.86)
N	10.44	13.13	76.43	12.41	3.88	83.71	-1.97	9.26	-7.28
	(1.42)	(1.57)	(2.26)	(0.15)	(0.09)	(0.17)	(1.43)	(1.57)	(2.26)
Female									
E	96.00	2.56	1.44	94.23	1.51	4.26	1.76	1.05	-2.82
	(0.25)	(0.17)	(0.14)	(0.04)	(0.02)	(0.04)	(0.25)	(0.17)	(0.15)
U	59.50	31.41	9.09	40.73	29.65	29.62	18.77	1.76	-20.53
	(2.90)	(2.15)	(1.83)	(0.44)	(0.42)	(0.41)	(2.93)	(2.19)	(1.88)
N	10.77	14.68	74.55	9.94	2.56	87.50	0.83	12.12	-12.95
	(0.96)	(1.32)	(1.75)	(0.09)	(0.05)	(0.10)	(0.97)	(1.32)	(1.76)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses.

Table 2.22: 4-Months subjective and actual transition probabilities (by education, gender)

	Subjective E	Subjective U	Subjective N	Actual E	Actual U	Actual N	Subjective – Actual E	Subjective – Actual U	Subjective – Actual N
Age									
25–29									
E	95.91	2.63	1.47	93.87	2.06	4.07	2.04	0.56	-2.60
	(0.46)	(0.29)	(0.25)	(0.08)	(0.05)	(0.07)	(0.47)	(0.30)	(0.26)
U	65.73	24.94	9.33	42.93	30.63	26.43	22.80	-5.70	-17.10
	(5.91)	(3.67)	(3.66)	(0.75)	(0.70)	(0.67)	(5.96)	(3.74)	(3.72)
N	11.13	22.72	66.15	16.36	5.20	78.44	-5.23	17.53	-12.29
	(2.38)	(4.99)	(6.10)	(0.27)	(0.17)	(0.30)	(2.40)	(4.99)	(6.10)
30–39									
E	96.33	2.39	1.28	95.23	1.61	3.16	1.10	0.78	-1.88
	(0.29)	(0.19)	(0.18)	(0.05)	(0.03)	(0.04)	(0.29)	(0.20)	(0.18)
U	69.27	24.70	6.03	44.08	31.49	24.43	25.19	-6.79	-18.40
	(3.60)	(2.93)	(2.71)	(0.58)	(0.54)	(0.50)	(3.65)	(2.98)	(2.76)
N	14.77	15.81	69.41	12.95	3.57	83.48	1.82	12.25	-14.07
	(2.34)	(2.44)	(3.50)	(0.17)	(0.09)	(0.19)	(2.34)	(2.44)	(3.51)
40–49									
E	96.35	2.61	1.05	95.80	1.44	2.75	0.54	1.16	-1.71
	(0.32)	(0.20)	(0.16)	(0.05)	(0.03)	(0.04)	(0.32)	(0.20)	(0.17)
U	54.06	36.72	9.22	43.97	31.99	24.04	10.09	4.73	-14.82
	(4.06)	(3.03)	(2.22)	(0.62)	(0.59)	(0.54)	(4.11)	(3.08)	(2.29)
N	12.73	16.21	71.06	11.01	2.87	86.12	1.73	13.34	-15.06
	(1.49)	(1.49)	(2.39)	(0.16)	(0.08)	(0.17)	(1.50)	(1.50)	(2.39)
50–54									
E	96.65	2.14	1.20	95.66	1.33	3.01	0.99	0.81	-1.80
	(0.32)	(0.20)	(0.21)	(0.06)	(0.04)	(0.05)	(0.33)	(0.20)	(0.22)
U	66.04	30.68	3.28	40.29	34.35	25.35	25.75	-3.68	-22.07
	(6.51)	(5.85)	(1.24)	(0.82)	(0.81)	(0.74)	(6.56)	(5.91)	(1.44)
N	7.80	13.82	78.38	8.71	2.41	88.88	-0.91	11.41	-10.51
	(1.41)	(2.44)	(2.89)	(0.17)	(0.09)	(0.19)	(1.42)	(2.44)	(2.90)
55–60									
E	95.04	2.59	2.37	94.72	1.35	3.93	0.32	1.24	-1.56
	(0.56)	(0.35)	(0.40)	(0.07)	(0.03)	(0.06)	(0.56)	(0.35)	(0.40)
U	47.81	49.09	3.09	37.68	34.39	27.93	10.13	14.70	-24.84
	(4.40)	(4.38)	(0.83)	(0.80)	(0.80)	(0.75)	(4.47)	(4.45)	(1.12)
N	6.68	7.70	85.63	6.61	1.70	91.69	0.07	6.00	-6.07
	(1.00)	(1.03)	(1.59)	(0.12)	(0.06)	(0.13)	(1.00)	(1.03)	(1.60)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses.

Table 2.23: 4-Months subjective and actual transition probabilities (by age)

	Year								
	Subjective			Actual			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
	2014								
E	95.35	3.16	1.49	95.19	1.66	3.15	0.16	1.50	-1.66
	(0.46)	(0.33)	(0.24)	(0.08)	(0.05)	(0.06)	(0.47)	(0.33)	(0.25)
U	56.03	38.28	5.69	39.07	35.59	25.34	16.96	2.69	-19.65
	(5.38)	(4.44)	(1.47)	(0.80)	(0.80)	(0.73)	(5.44)	(4.51)	(1.64)
N	6.78	14.03	79.18	10.06	3.51	86.43	-3.27	10.52	-7.24
	(1.45)	(2.54)	(3.28)	(0.21)	(0.13)	(0.25)	(1.47)	(2.54)	(3.29)
	2015								
E	95.57	2.54	1.90	95.08	1.63	3.28	0.48	0.90	-1.39
	(0.49)	(0.25)	(0.34)	(0.06)	(0.04)	(0.05)	(0.50)	(0.25)	(0.35)
U	55.97	38.29	5.74	40.47	34.63	24.90	15.50	3.67	-19.16
	(4.77)	(4.15)	(2.13)	(0.66)	(0.65)	(0.59)	(4.81)	(4.20)	(2.21)
N	8.89	15.72	75.38	10.52	3.33	86.15	-1.63	12.39	-10.76
	(2.36)	(2.88)	(3.37)	(0.17)	(0.10)	(0.19)	(2.37)	(2.88)	(3.38)
	2016								
E	96.03	2.81	1.16	95.15	1.58	3.27	0.88	1.22	-2.11
	(0.42)	(0.34)	(0.19)	(0.06)	(0.04)	(0.05)	(0.43)	(0.34)	(0.20)
U	65.83	31.86	2.32	41.91	33.24	24.85	23.92	-1.39	-22.53
	(4.96)	(4.82)	(0.94)	(0.69)	(0.67)	(0.61)	(5.01)	(4.86)	(1.11)
N	10.75	13.71	75.54	10.61	3.23	86.16	0.14	10.48	-10.62
	(2.12)	(2.20)	(3.25)	(0.17)	(0.10)	(0.19)	(2.13)	(2.20)	(3.26)
	2017								
E	96.41	2.25	1.34	95.25	1.48	3.27	1.16	0.78	-1.93
	(0.40)	(0.22)	(0.29)	(0.06)	(0.03)	(0.05)	(0.40)	(0.22)	(0.30)
U	67.61	27.36	5.04	44.68	30.36	24.96	22.92	-3.00	-19.93
	(4.63)	(3.76)	(2.14)	(0.75)	(0.71)	(0.66)	(4.69)	(3.82)	(2.23)
N	14.31	16.23	69.47	11.08	2.71	86.21	3.22	13.52	-16.74
	(1.75)	(2.78)	(3.70)	(0.18)	(0.09)	(0.20)	(1.75)	(2.78)	(3.71)
	2018								
E	96.27	2.39	1.34	95.46	1.31	3.23	0.82	1.08	-1.89
	(0.40)	(0.27)	(0.21)	(0.06)	(0.03)	(0.05)	(0.40)	(0.27)	(0.22)
U	63.83	27.18	9.00	44.25	29.83	25.92	19.58	-2.65	-16.92
	(5.98)	(3.85)	(3.46)	(0.80)	(0.74)	(0.71)	(6.03)	(3.92)	(3.53)
N	10.67	9.59	79.74	10.85	2.49	86.65	-0.19	7.10	-6.91
	(1.98)	(1.22)	(2.66)	(0.18)	(0.09)	(0.20)	(1.99)	(1.23)	(2.67)
	2019								
E	96.82	1.94	1.23	94.96	1.68	3.36	1.87	0.26	-2.13
	(0.31)	(0.18)	(0.19)	(0.07)	(0.04)	(0.06)	(0.31)	(0.18)	(0.20)
U	61.88	25.73	12.39	45.12	28.45	26.43	16.76	-2.72	-14.03
	(6.15)	(4.48)	(5.80)	(0.93)	(0.86)	(0.83)	(6.22)	(4.56)	(5.86)
N	11.01	15.81	73.19	10.96	2.67	86.38	0.05	13.14	-13.19
	(1.67)	(2.83)	(3.43)	(0.21)	(0.11)	(0.23)	(1.68)	(2.83)	(3.44)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses.

Table 2.24: 4-Months subjective and actual transition probabilities (by year)

Household income

	Subjective			Actual			Subjective – Actual		
	E	U	N	E	U	N	E	U	N
				Less than $30,000					
E	90.84	5.43	3.73	91.22	3.22	5.56	-0.39	2.22	-1.83
	(0.74)	(0.48)	(0.42)	(0.10)	(0.06)	(0.08)	(0.75)	(0.48)	(0.43)
U	62.13	30.72	7.15	37.56	33.95	28.50	24.58	-3.23	-21.35
	(3.23)	(2.65)	(1.86)	(0.48)	(0.47)	(0.44)	(3.27)	(2.69)	(1.92)
N	10.50	17.47	72.03	8.91	3.42	87.66	1.58	14.05	-15.63
	(1.27)	(1.61)	(2.14)	(0.11)	(0.07)	(0.13)	(1.27)	(1.61)	(2.14)
				$30,000 – $49,000					
E	96.73	2.27	1.00	94.02	1.99	3.99	2.71	0.28	-2.99
	(0.29)	(0.22)	(0.16)	(0.07)	(0.04)	(0.06)	(0.30)	(0.23)	(0.17)
U	57.33	36.01	6.66	42.59	32.40	25.01	14.74	3.60	-18.35
	(5.32)	(4.18)	(2.35)	(0.70)	(0.67)	(0.61)	(5.37)	(4.23)	(2.43)
N	13.46	14.64	71.89	10.78	2.87	86.34	2.68	11.77	-14.45
	(2.19)	(2.97)	(3.98)	(0.17)	(0.09)	(0.19)	(2.20)	(2.98)	(3.98)
				$50,000 – $99,000					
E	97.30	1.82	0.88	95.64	1.36	3.00	1.66	0.46	-2.12
	(0.21)	(0.14)	(0.14)	(0.04)	(0.02)	(0.03)	(0.21)	(0.14)	(0.14)
U	64.91	30.09	5.00	47.63	29.49	22.88	17.27	0.60	-17.88
	(3.54)	(2.67)	(2.30)	(0.63)	(0.59)	(0.54)	(3.60)	(2.74)	(2.37)
N	9.76	10.17	80.07	12.54	2.85	84.62	-2.77	7.32	-4.55
	(1.19)	(1.66)	(2.24)	(0.16)	(0.08)	(0.18)	(1.20)	(1.67)	(2.24)
				More than $100,000					
E	97.15	1.82	1.03	96.80	0.88	2.32	0.35	0.94	-1.29
	(0.22)	(0.12)	(0.17)	(0.04)	(0.02)	(0.03)	(0.23)	(0.12)	(0.17)
U	59.50	35.09	5.41	47.64	31.65	20.71	11.86	3.43	-15.30
	(5.39)	(4.91)	(1.89)	(0.84)	(0.79)	(0.69)	(5.45)	(4.97)	(2.01)
N	8.90	7.87	83.23	12.02	2.24	85.74	-3.11	5.63	-2.52
	(1.38)	(1.15)	(2.14)	(0.19)	(0.09)	(0.21)	(1.40)	(1.15)	(2.15)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Household income: total annual pre-tax income of all household members (older than 15 years), from all sources including employment, business, farm or rent, pensions, financial assets, government transfers and benefits.

Table 2.25: 4-Months subjective and actual transition probabilities (by income)

E Average Marginal Effect of Education on Expectation Bias

As described in the main text, the average expectation biases reported in Table 2.2 might be blurred by compositional differences across education groups. To combat this concern, we compute the average marginal effects of education on the biases for all transitions. Table 2.26 reports the estimated effects for the transitions out of employment, Table 2.27 for transitions out of unemployment and Table 2.28 for transitions out of non-participation. In addition to the results from Table 2.3, these tables also report the effects for different sets of control variables. To obtain these results we perform the following steps: First, we chose a set of control variables (x) always containing education and the intercept. Second, in CPS, we fit the Probit model

$$P(Y_i = 1|x_i) = \Phi(x_i'\beta)$$

for each 3 and 9 month transition rate. In this step we use the CPS sample weights WTFINL. Third, we use the estimated coefficients of the previous 18 regressions to generate fitted values for 3 and 9 months transition rates for each individual in the SCE. We interpolate linearly to obtain predicted 4 months transition rates for the relevant flows for each individual. Fourth, we subtract the predicted transition rates from the stated subjective expectations to obtain individual-level biases. Fifth, we perform a linear regression analogously to step 2, with weights from the SCE re-weighted to match the CPS targets as described in the baseline exercise. This regression is of the form

$$z_{iY} = x_i'\gamma_Y,$$

where Y is one of the 9 biases (regarding the different flows), and x contains the identical variables as in step 2. Finally, we compute the average marginal effect and the associated standard errors by evaluating the estimated equation at the means of all variables and by using the delta method.

	Mean	Regressions					
				EE			
High school or less	1.82 (0.45)	1.82 (0.45)	1.86 (0.45)	1.87 (0.45)	2.11 (0.45)	2.09 (0.44)	2.35 (0.42)
Some college	0.85 (0.26)	0.85 (0.25)	0.86 (0.25)	0.83 (0.25)	0.83 (0.25)	0.83 (0.25)	1.04 (0.25)
College and higher	0.27 (0.13)	0.27 (0.13)	0.26 (0.13)	0.24 (0.13)	0.21 (0.13)	0.16 (0.13)	0.21 (0.17)
				EU			
High school or less	0.71 (0.29)	0.71 (0.29)	0.68 (0.29)	0.69 (0.29)	0.69 (0.29)	0.69 (0.29)	0.45 (0.27)
Some college	0.77 (0.15)	0.77 (0.15)	0.76 (0.15)	0.78 (0.15)	0.77 (0.15)	0.77 (0.15)	0.64 (0.14)
College and higher	1.22 (0.09)	1.22 (0.09)	1.23 (0.09)	1.24 (0.09)	1.24 (0.09)	1.27 (0.09)	1.40 (0.12)
				EN			
High school or less	-2.53 (0.26)	-2.53 (0.26)	-2.54 (0.26)	-2.56 (0.26)	-2.79 (0.26)	-2.77 (0.25)	-2.79 (0.26)
Some college	-1.62 (0.19)	-1.62 (0.18)	-1.62 (0.18)	-1.61 (0.18)	-1.60 (0.18)	-1.59 (0.18)	-1.68 (0.18)
College and higher	-1.49 (0.09)	-1.49 (0.08)	-1.49 (0.08)	-1.48 (0.08)	-1.46 (0.09)	-1.43 (0.09)	-1.61 (0.10)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	10550	10550	10550	10550	10549	10549	10509
		0.00	0.00	0.01	0.01	0.01	0.02
R^2		0.00	0.00	0.00	0.00	0.01	0.01
		0.00	0.00	0.01	0.02	0.02	0.03

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of employment. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 2.26: Average marginal effect of education on 4-months bias for employed

	Mean	Regressions					
	UE						
High school or less	21.72 (4.26)	21.72 (4.24)	21.96 (4.13)	21.80 (3.83)	22.63 (3.75)	23.18 (3.46)	23.70 (3.42)
Some college	21.41 (2.78)	21.41 (2.72)	20.91 (2.72)	21.06 (2.68)	21.58 (2.74)	21.35 (2.69)	22.32 (2.70)
College and higher	10.56 (2.67)	10.56 (2.60)	11.11 (2.62)	11.62 (2.65)	11.63 (2.65)	10.70 (2.77)	13.00 (2.78)
	UU						
High school or less	-2.82 (3.27)	-2.82 (3.25)	-2.76 (3.08)	-2.49 (2.79)	-1.62 (2.79)	-1.79 (2.74)	-2.43 (2.72)
Some college	0.13 (2.56)	0.13 (2.50)	0.34 (2.57)	0.17 (2.48)	0.58 (2.50)	0.70 (2.47)	0.09 (2.45)
College and higher	4.79 (2.52)	4.79 (2.45)	4.21 (2.46)	3.56 (2.48)	3.98 (2.48)	4.33 (2.53)	4.01 (2.60)
	UN						
High school or less	-18.90 (2.44)	-18.90 (2.41)	-19.20 (2.26)	-19.34 (2.14)	-21.19 (2.05)	-21.57 (1.82)	-21.51 (1.81)
Some college	-21.54 (1.15)	-21.54 (1.03)	-21.24 (1.09)	-21.21 (1.09)	-22.16 (1.14)	-22.06 (1.15)	-22.38 (1.17)
College and higher	-15.35 (1.01)	-15.35 (0.87)	-15.33 (0.90)	-15.17 (0.96)	-15.61 (0.97)	-15.13 (1.01)	-16.99 (0.99)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	364	364	364	364	364	364	364
		0.02	0.03	0.08	0.08	0.09	0.10
R^2		0.01	0.02	0.09	0.10	0.10	0.11
		0.02	0.05	0.10	0.10	0.13	0.15

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of unemployment. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 2.27: Average marginal effect of education on 4-months bias for unemployed

	Mean	Regressions					
	NE						
High school or less	1.33	1.33	1.25	1.46	1.71	1.67	1.25
	(1.40)	(1.39)	(1.37)	(1.37)	(1.38)	(1.37)	(1.28)
Some college	-0.28	-0.28	-0.29	-0.05	-0.05	-0.04	0.29
	(0.92)	(0.90)	(0.90)	(0.90)	(0.91)	(0.90)	(0.92)
College and higher	-2.81	-2.81	-2.62	-2.58	-2.71	-2.48	-0.81
	(1.15)	(1.13)	(1.14)	(1.15)	(1.15)	(1.15)	(1.28)
	NU						
High school or less	12.44	12.44	12.40	12.64	12.78	12.65	11.90
	(1.88)	(1.88)	(1.83)	(1.77)	(1.77)	(1.64)	(1.63)
Some college	10.44	10.44	10.52	10.54	10.52	10.51	10.11
	(1.01)	(1.01)	(1.01)	(0.99)	(1.00)	(0.97)	(0.97)
College and higher	9.39	9.39	9.48	9.17	9.15	9.66	11.69
	(1.07)	(1.07)	(1.08)	(1.09)	(1.09)	(1.10)	(1.37)
	NN						
High school or less	-13.77	-13.77	-13.65	-14.10	-14.48	-14.31	-13.12
	(2.51)	(2.51)	(2.42)	(2.37)	(2.37)	(2.22)	(2.15)
Some college	-10.16	-10.16	-10.23	-10.49	-10.45	-10.44	-10.40
	(1.48)	(1.47)	(1.47)	(1.45)	(1.46)	(1.40)	(1.43)
College and higher	-6.59	-6.59	-6.86	-6.59	-6.42	-7.18	-10.86
	(1.70)	(1.69)	(1.71)	(1.71)	(1.71)	(1.72)	(1.96)
Additional control variables							
Year			x	x	x	x	x
Age				x	x	x	x
Gender					x	x	x
Race						x	x
Income							x
N	1474	1474	1474	1474	1474	1474	1468
		0.01	0.01	0.02	0.02	0.03	0.04
R^2		0.00	0.01	0.03	0.04	0.10	0.11
		0.01	0.02	0.03	0.03	0.08	0.10

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. Average marginal effect of education on the bias for transitions out of nonparticipation. Actual transition rates are estimated in CPS and used to generate fitted values in the SCE sample.

Table 2.28: Average marginal effect of education on 4-months bias for non-participants

F Average Marginal Effect of Duration in Labor Market State on Expectation Bias

This section repeats the exercise outlined in Section E. Therefore, we focus here on the definition of the variables in CPS and SCE. To compute job tenure in CPS, we use the Job Tenure & Occupational Mobility Supplement as well as the monthly datasets. Since the supplement is only available in January every second year, we use January 2014, 2016, and 2018 as the main sample. From the tenure supplement we use the information on the "length of time worked at current job in years" (JTYEARS) as well as the weights (JTSUPPWT). We group tenure into 5 different bins and check if the reported job tenure aligns with the reported employment status of the preceding months. If the respondent reported to be unemployed or out of the labor force in the preceding two months, the tenure is set to the lowest duration bin. For all other bins, if the reported employment status contradicts the tenure information (i.e, if the respondent stated to be not employed during that time) it is discarded. In SCE we rely on the question L1 of the Labor Market Module, which asks about the month and year when the respondent started working at the main/current job. We apply the same grouping and correction using the reported employment status as with the CPS data.

For unemployed individuals, we use the variable DURUNEMP from the regular monthly CPS datasets. This variable indicates the "continuous weeks unemployed". Since this variable is available each month, we use our baseline CPS dataset and the corresponding basic individual weight WTFINL. We convert weeks into months by multiplying with 4.345. Analogously, we consider question Q16 from the SCE core survey asking about the unemployment duration in months. In both cases, we check if the reported unemployment duration is consistent with the reported employment status from the preceding interviews. If not, we discard the observation. Additionally, we group the duration into 4 categories.

For out-of-the-labor force individuals, we use yet another CPS sample. This time we rely on the weights and four variables from the Annual Social and Economic Supplement (ASEC) between 2014 and 2019. This supplement is conduced every March for the outgoing rotation groups, i.e., for respondents in their 4th or 8th interview. We use the variables WNLWNILF ("When last worked for pay (NILF last week)"), WKSWORK1 ("Weeks worked last year"), WKSUNEM1 ("Weeks unemployed last year"), and NWLOOKWK ("Weeks looked for work last year (didn't work)"). We divide individuals into two groups based on non-participation durations being shorter or longer than one year. For 3 month transition rates, we consider the transitions from interview 5 to 8, such that respondents are part of the ASEC sample at the time of the 8th interview. We define the two groups as follows: The duration at the time of the

5th interview is shorter than one year, if the respondent reported to be employed or unemployed in any interview in the preceding 12 months or if the person reported to have worked last year or looked any number of weeks for a job, both at the time of the 8th interview. If these three conditions are all not met, the duration is set to be longer than one year. For the 9 month transition rate, we consider the change in the labor market state from interview 4 to 5. For this case, we define a duration of less than one year, if the respondent was employed or unemployed in any of the first three interviews, reported to have worked in the previous 12 months (WNLWNILF), or the sum of WKSWORK1, WKSUNEM1, and NWLOOKWK is larger than 8.428. Since the ASEC questions ask about the preceding calendar year, this condition guarantees that the respondent has at least worked or search 1 day in the past 12 months at the time of the interview. Again, we set the duration to "longer than one year", if all these conditions are not met. We use ASECWT to weight the observations. Luckily, we can directly use question L7 of the Labor Market Module asking about the month and year when the respondent started working at the last job. Again, we assign observations to the shorter duration if the implied duration is below one year or if the respondent stated to be employed or unemployed in any of the preceding interviews. If the implied duration is longer than one year and the respondent always reported to be out of the labor force, it is assigned to be in the second group.

Finally, note that we re-weight the SCE weights targeting the age education shares by employment status of the corresponding CPS sample.

G Additional Learning Results

To check the robustness of our learning results, we consider an additional set of questions that allows us to relate the duration of the current individual labor market state to the perceived and actual transitions. This exercise is inspired by (and partly replicates) Table 2 of Mueller et al. (2019). Table 2.29 focuses on employed workers: in their first interview employed workers are asked about their job tenure (Q37). Every month, and therefore also in their first interview, questions Q13new and Q14new ask about the subjective probability that the respondent looses or voluntarily leaves the main/current job during the next 12 months. To compare theses expectations to actual outcomes, we restrict the sample to only those individuals which are in the sample for all the next 11 months. This allows us to compute the share of workers who are at some point within the next 11 months unemployed, not in the labor force, or work for a different employer. While this does not match the horizon of the expectation question, it provides a reference point. Regarding the perceived job-loss probability as the closed match to the EU transitions of Table 2.4, we confirm that subjective expectations get more precise as tenure increases.

Turning to unemployed workers, Table 2.30 reports the average perceived and actual job-finding probability by unemployment duration. This table is directly comparable to Table 2 of Mueller et al. (2019) but features a larger sample size and therefore displays slightly different values. Exploiting that unemployed workers are asked about their unemployment duration (Q18New) as well as their perceived job-finding rate for a 3 month horizon, we mirror the previous exercise: we restrict the sample to all currently unemployed workers reporting the duration and which are in the sample the following three months. This allows us to compute the actual job finding probability by computing the share of workers which report to be employed at least once during these interviews. Except for the long-term unemployed, we find little adjustment in the perceived job-finding rate, while the actual job-finding rate drops substantially. This implies a larger bias for longer unemployment duration and is therefore in line with the results for UE from Table 2.4.

Finally, we consider workers currently being out of the labor-force. We apply the same procedure as for the unemployed: Question Q19 asks about the non-employment duration and Q21new about the probability of starting to look for a job in the next three months. We restrict the sample analogously to before and compute the share of respondents who are employed or unemployed at least once in the following three interviews. Sadly, the sample size is not sufficiently large to obtain any meaningful results. If any, we find that the actual as well as the perceived probability of starting to search for a job declines in the non-employment duration.

Tenure	Perceived Job-Loss Probability	Perceived Job-Quit Probability	Actual Job-Separation Probability	Sample Size
Full sample	15.25 (0.66)	22.43 (0.82)	13.09 (1.10)	1946
< 1 month	33.85 (9.66)	27.30 (10.03)	49.96 (11.41)	34
$1-6$ months	18.91 (4.26)	24.99 (4.27)	30.61 (7.56)	93
$6-12$ months	18.44 (2.22)	34.37 (3.67)	20.63 (4.30)	116
$1-5$ years	16.37 (0.98)	28.21 (1.49)	12.63 (1.63)	656
> 5 years	13.28 (0.88)	17.19 (0.94)	9.71 (1.41)	1047

Sample: Employed individuals with age 25-60 years, non-school or -college which reported job tenure and are in the sample for all 12 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about job loss and quit in the next 12 months and actual separations within the following 11 months in % by job tenure.

Table 2.29: Average perceived and actual job separation probabilities by job tenure

Unemployment Duration	Perceived Job-Finding Probability	Actual Job-Finding Probability	Sample Size
Full sample	50.54 (1.95)	38.89 (3.06)	1318
$0-3$ months	64.25 (3.37)	61.34 (4.92)	362
$4-6$ months	54.40 (3.51)	44.79 (6.50)	191
$7-12$ months	56.25 (3.79)	38.52 (5.62)	217
≥ 13 months	38.96 (2.67)	23.68 (3.65)	548

Sample: Unemployed individuals with age 25-60 years, non-school or -college which reported unemployment duration and are in the sample for the following 3 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about job finding in the next 3 months and actual job finding rates within the following 3 months in % by unemployment duration.

Table 2.30: Average perceived and actual job finding probability by unemployment duration

Non-employment Duration	Perceived Job-Search Probability	Actual Job-Search Probability	Sample Size
Full sample	30.72 (3.44)	29.35 (4.30)	323
$0-3$ months	68.75 (5.03)	41.89 (13.09)	34
$4-6$ months	48.87 (10.40)	45.61 (19.25)	20
$7-12$ months	44.40 (6.85)	51.04 (13.73)	39
≥ 13 months	22.79 (3.17)	23.70 (4.61)	230

Sample: Out-of-labor force individuals with age 25-60 years, non-school or -college which reported non-employment duration and are in the sample for the following 3 interviews; Period: 01/2013-12/2019. Source: SCE. Standard errors in parentheses. Subjective expectations about starting to search for a job in the next 3 months and actual job search rates within the following 3 months in % by non-employment duration.

Table 2.31: Average perceived and actual job finding probability by unemployment duration

Age	EE	EU	EN	UE	UU	UN	NE	NU	NN
25–29	2.25 (0.44)	0.45 (0.28)	-2.70 (0.24)	24.04 (4.62)	-5.21 (3.43)	-18.94 (2.67)	-4.87 (1.91)	16.51 (4.36)	-11.55 (4.78)
30–39	1.21 (0.28)	0.79 (0.19)	-1.99 (0.17)	27.14 (3.72)	-6.77 (2.94)	-20.35 (2.30)	2.13 (2.54)	12.93 (2.24)	-15.06 (3.41)
40–49	0.72 (0.31)	1.13 (0.20)	-1.85 (0.16)	13.14 (3.53)	3.97 (2.69)	-17.30 (1.91)	1.99 (1.48)	12.83 (1.47)	-14.81 (2.34)
50–54	1.25 (0.33)	0.74 (0.20)	-1.98 (0.21)	26.24 (6.14)	-2.37 (5.41)	-23.92 (1.36)	-0.18 (1.48)	11.45 (2.38)	-11.27 (2.90)
55–60	0.72 (0.53)	1.10 (0.33)	-1.81 (0.39)	11.20 (4.46)	14.53 (4.39)	-25.99 (1.42)	0.48 (1.06)	6.55 (1.08)	-7.01 (1.65)

Sample: Individuals with age 25-60 years, non-school or -college; Period: 07/2014-11/2019. Source: SCE and CPS. Standard errors in parentheses. E: employment, U: unemployment, N: not in the labor force. XY: Transition from current labor market state X to future state Y. Example: "UE" represents the bias in unemployed workers' expectation to be employed in four months.

Table 2.32: Conditional expectation bias, by age

H Input to Calibration

H.1 CPS Welfare Benefits

We use data from the 2015–2019 waves of the March supplement of the CPS. In this supplement, individuals report their income from various sources during the preceding 12 months. Aggregate welfare income is computed as total annual income reported by welfare recipients. It includes income from public assistance, survivor's and disability benefits, worker's compensation (due to job-related injury or illness), educational assistance, child support, veteran's benefits, and income or assistance from other sources. The sample of welfare recipients includes non-retired individuals (aged 25-60 years) who did not work nor searched for a job in the preceding 12 months and who did not received wage, or business income, or income related to retirement. Aggregate annual labor earnings are computed from the sample of individuals who worked full-time, and were formally employed for the whole year, and who did not received any income from self-employment or retirement. We define total labor earnings as wage and salary income. Average welfare (labor) income is computed as aggregate welfare (labor) income divided by the number of welfare recipients (workers).

H.2 Conversion from 4-Months to 3-Months Frequency

We implement the following approach to convert the 4-months subjective transition probabilities into 3-months transition probabilities. Let by p_h^{4m} denote the 4-months transition probability matrix for skill group h. The matrix has dimension 3×3. We assume that labor market transitions follow a Markov Chain with monthly transition probabilities. Thus, the four months transition matrix, p_h^{4m}, is identical to the (unobserved) 1-month transition matrix multiplied four times with itself. Let by p_h^{1m} denote the 1-month transition matrix. We obtain p_h^{1m} by solving the following 9-dimensional system of equations:

$$vec\left[\left(p_h^{1m}\right)^4 - p_h^{4m}\right] = 0$$

where *"vec"* vectorizes the 3x3 array inside the square brackets. Lastly, we obtain the 3-months transition probabilities as $(p_h^{1m})^3$. The values of the 3-months subjective and actual transition probabilities are given by:

$$\widehat{p}_{h_L} = \begin{pmatrix} 96.16 & 2.43 & 1.41 \\ 52.83 & 38.71 & 8.46 \\ 6.58 & 13.69 & 79.73 \end{pmatrix} \quad \widehat{p}_{h_M} = \begin{pmatrix} 96.69 & 2.01 & 1.31 \\ 54.29 & 42.70 & 3.00 \\ 6.98 & 12.20 & 80.83 \end{pmatrix} \quad \widehat{p}_{h_H} = \begin{pmatrix} 97.51 & 1.85 & 0.64 \\ 49.03 & 47.40 & 3.57 \\ 7.52 & 10.63 & 81.86 \end{pmatrix}$$

$$p_{h_L} = \begin{pmatrix} 93.83 & 2.02 & 4.15 \\ 37.58 & 33.66 & 28.76 \\ 8.39 & 2.82 & 88.79 \end{pmatrix} \quad p_{h_M} = \begin{pmatrix} 95.40 & 1.50 & 3.10 \\ 39.91 & 34.60 & 25.50 \\ 10.01 & 3.42 & 86.57 \end{pmatrix} \quad p_{h_H} = \begin{pmatrix} 96.89 & 0.90 & 2.21 \\ 45.40 & 35.14 & 19.46 \\ 12.78 & 2.82 & 84.40 \end{pmatrix}$$

H.3 PSID: Estimation of Labor Productivity Process

To estimate the parameters of the stochastic labor productivity process, we use annual data from PSID for the time period 1968-1997. Our sample consists of household heads. We only include individuals who belong to the SRC-sample. We drop observations where (i) the household head is younger than 25 years and older than 60 years, (ii) there is no information on education, (ii) annual hours are below 520 hours (10h/week), or above 5110 hours (14h/day), (iv) reported labor earnings are zero, (v) the household head is female, (vi) hourly labor earnings are below $\underline{w}$ and above $\bar{w}$, where $\underline{w} = 2$ and $\bar{w} = 400$ in 1993, as in Guvenen (2009), and in the other years $\underline{w}$ and $\bar{w}$ grow at the same rate as nominal wages according to the Federal Reserve Bank of St. Louis' FRED database. Lastly, we deflate nominal hourly wages by using the series of the "Consumer Price Index for All Urban Consumers" from the FRED database. Hourly wages are computed as annual labor income (variable code "V3863" in year 1975) divided by annual hours worked ("V3823").

In the first step of the estimation procedure, we compute residual wages by filtering out the effect of observables. More concretely, we regress *log*-hourly wages on age dummies $(25-30, 30-40, 40-50, 50-60)$, education dummies (high school or less, some college, college degree and higher), interaction of age and education dummies and year dummies. Then, we recover the wage residuals - which are equal to labor productivity in the model. The underlying empirical process for residual wages is assumed to be

$$\begin{aligned} w_t &= z_t + \epsilon_t \\ & \quad z_t = \rho z_{t-1} + \eta_t \end{aligned}$$

where $E(\epsilon_t) = E(\eta_t) = 0$, $Var(\epsilon_t) = \sigma_\epsilon^2$, $Var(\eta_t) = \sigma_\eta^2$. The identification of the parameters $\rho, \sigma_\epsilon^2, \sigma_\eta^2$ is based on the variance-(auto)covariance matrix of the wage process. The variance is defined as $\sigma_{tt} \equiv Cov(w_t, w_t) = E(w_t w_t) - E(w_t)E(w_t)$ and it is equal to

$$\sigma_{tt} = \frac{1}{1-\rho^2}\sigma_\eta^2 + \sigma_\epsilon^2$$

The auto-covariance is defined as $\sigma_{t,t+j} \equiv Cov(w_t, w_{t+j}) = E(w_t w_{t+j}) - E(w_t)E(w_{t+j})$, where $j > 0$, and it is given by:

$$\sigma_{t,t+j} = \frac{\rho^j}{1-\rho^2}\sigma_\eta^2$$

$\sigma_{t,t}$ and $\sigma_{t,t+j}$ are independent of time t (because of time-invariant variances), thus, we write:

$$\sigma = \frac{1}{1-\rho^2}\sigma_\eta^2 + \sigma_\epsilon^2 \qquad \sigma_j = \frac{\rho^j}{1-\rho^2}\sigma_\eta^2$$

where j denotes the lag. The parameters of the stochastic process: $\rho, \sigma_\epsilon^2, \sigma_\eta^2$ are identified as follows: Take σ_j and σ_{j+1}, where $j > 0$. The ratio between the two is given by

$$\frac{\sigma_{j+1}}{\sigma_j} = \frac{\frac{\rho^{j+1}}{1-\rho^2}\sigma_\eta^2}{\frac{\rho^j}{1-\rho^2}\sigma_\eta^2} = \frac{\rho^{j+1}}{\rho^j} = \rho$$

and it identifies ρ. Given ρ, any σ_j:

$$\sigma_j = \frac{\rho^j}{1-\rho^2}\sigma_\eta^2$$

identifies σ_η^2. Lastly, given ρ and σ_η^2, the expression for σ:

$$\sigma = \frac{1}{1-\rho^2}\sigma_\eta^2 + \sigma_\epsilon^2$$

identifies σ_ϵ^2. The estimation strategy is based on minimizing the distance between the (empirical) covariance matrix of income residuals and the (theoretical) counterpart implied by the income process. Let $\hat{y}_{it}$ denote the income residual, obtained from regressing the period-t wage of individual i on observables (see above). Define $\hat{y}_i \equiv \left(\hat{y}_{i1}, \hat{y}_{i2}, ..., \hat{y}_{iT}\right)$ and compute

$$\hat{y}_i'\hat{y}_i = \begin{pmatrix} \hat{y}_{i1}^2 & \hat{y}_{i1}\hat{y}_{i2} & ... & \hat{y}_{i1}\hat{y}_{iT} \\ \hat{y}_{i2}\hat{y}_{i1} & \hat{y}_{i2}^2 & ... & \hat{y}_{i2}\hat{y}_{iT} \\ ... & ... & ... & \\ \hat{y}_{iT}\hat{y}_{i1} & \hat{y}_{iT}\hat{y}_{i2} & ... & \hat{y}_{iT}^2 \end{pmatrix}$$

Build average across individuals (taking into account that the panel may be unbalanced; that is, the number of individuals that contribute to the moments may differ across moments)

$$\hat{y}'\hat{y} = \begin{pmatrix} \hat{y}_1^2 & \hat{y}_1\hat{y}_2 & ... & \hat{y}_1\hat{y}_T \\ \hat{y}_2\hat{y}_1 & \hat{y}_2^2 & ... & \hat{y}_2\hat{y}_T \\ ... & ... & ... & \\ \hat{y}_T\hat{y}_1 & \hat{y}_T\hat{y}_2 & ... & \hat{y}_T^2 \end{pmatrix} = \begin{pmatrix} \sum_i \hat{y}_{i1}^2/N_{11} & \sum_i \hat{y}_{i1}\hat{y}_{i2}/N_{12} & ... & \sum_i \hat{y}_{i1}\hat{y}_{iT}/N_{1T} \\ \sum_i \hat{y}_{i2}\hat{y}_{i1}/N_{21} & \sum_i \hat{y}_{i2}^2/N_{22} & ... & \sum_i \hat{y}_{i2}\hat{y}_{iT}/N_{2T} \\ ... & ... & ... & \\ \sum_i \hat{y}_{iT}\hat{y}_{i1}/N_{T1} & \sum_i \hat{y}_{iT}\hat{y}_{i2}/N_{T2} & ... & \sum_i \hat{y}_{iT}^2/N_{TT} \end{pmatrix}$$

where $\hat{y}_\tau^2$ is the sample variance of period τ; $\hat{y}_\tau \hat{y}_{\tau+s}$ is the s-order sample covariance between observations of periods τ and $\tau+s$; and $N_{\tau\tau+s}$ is the number of individuals contributing to the estimation of the s-order covariance between periods τ and $\tau+s$.

Since, $\hat{y}_\tau \hat{y}_{\tau'} = \hat{y}_{\tau'} \hat{y}_\tau$, the effective number of moments is less than $T \times T$ but equal to the $\frac{T(T+1)}{2}$ elements of the upper-triangular matrix. Hence, the data moments m^d are given by the following vector of dimension $\frac{T(T+1)}{2} \times 1$

$$m^d = \begin{pmatrix} \hat{y}_1^2 \\ \hat{y}_1 \hat{y}_2 \\ ... \\ \hat{y}_1 \hat{y}_T \\ \hat{y}_2^2 \\ \hat{y}_2 \hat{y}_3 \\ ... \\ \hat{y}_2 \hat{y}_T \\ ... \\ \hat{y}_T^2 \end{pmatrix}$$

Let $\Theta = \left(\rho, \sigma_\eta^2, \sigma_\epsilon^2\right)$ be the parameters of the stochastic process and $m(\Theta)$ be the vector of model moments:

$$m(\Theta) = \begin{pmatrix} \sigma^2 \\ \sigma_1 \\ ... \\ \sigma_{T-1} \\ \sigma^2 \\ \sigma_1 \\ ... \\ \sigma_{T-1} \\ ... \\ \sigma^2 \end{pmatrix}$$

The model parameters, Θ are recovered by minimizing a squared distance function $\left[m(\Theta) - m^d\right]' \times W \times \left[m(\Theta) - m^d\right]$ where W is the weighting matrix with dimension $\frac{T(T+1)}{2} \times \frac{T(T+1)}{2}$. We follow Kaplan (2012) and use as weighting matrix a diagonal matrix with elements $n^{-1/2}$, where n is the number of observations used to construct the sample moment. In the estimation, we use a maximum number of 25 lags. We estimate the parameters of the stochastic process for the entire sample and separately for each skill group. Standard errors are obtain by bootstrap with 250 replications. The estimated parameters are reported in Table 2.33.

	ρ	σ_η^2	σ_ϵ^2
All	0.9653 (0.0040)	0.0138 (0.0018)	0.0739 (0.0041)
Low skill	0.9677 (0.0043)	0.0126 (0.0019)	0.0640 (0.0048)
Middle skill	0.9614 (0.0073)	0.0135 (0.0029)	0.0767 (0.0066)
High skill	0.9661 (0.0084)	0.0147 (0.0040)	0.0847 (0.0088)

Source: PSID. Standard errors in parentheses.

Table 2.33: Estimated coefficients of the labor productivity process

I PSID: Lifecycle Path of Income, Consumption and Wealth

We follow KMP and construct the measures of income, consumption and wealth as follows. Pre-tax income is constructed by adding, for each household and from all members, income from assets, earnings, and net profits from farm or business (ER71330, ER71398), transfers (ER71391, ER71419), and social security (ER71420, ER71422, ER71424). The codes in brackets refer to the variable name in the 2017 wave of the PSID.

Consumption expenditures includes expenditures on cars and other vehicles purchases, food at home and away (ER71487), clothing and apparel (ER71525), child care (ER71516), health care (ER71517), housing including rent and imputed rental services for owners (ER71491), utilities and transportation expenses (ER71503), education (ER71515), trips and recreation (ER71527, ER71526), electronics and IT equipment (ER71522). Imputed rents for home owners were computing using the value of main residence (ER66031) times an interest rate of 4%.

Net worth is defined as the value of households' assets minus debt. Assets include the value of farms and businesses (ER71429), checking and saving accounts (ER71435), stocks or bonds (ER71445), real estates (ER71481,ER71439) , vehicles (ER71447), individual retirement accounts (ER71455), other assets (ER71451). Debt include the value of debt on real estate and farms or businesses (ER71431, ER71441), student loans (ER71463), medical debt (ER71467), credit card debt (ER71459), legal debt (ER71471) and other debt (ER71475, ER71479)

All observations are aggregated using sample weights.

J Computational Algorithm

The numerical computation of the general equilibrium involves the following sequence of steps:

1. Specify a grid for individual assets, a.
2. Discretize the idiosyncratic productivity shocks as described below.
3. Use the labor market transition probabilities to compute the total labor supply in efficiency units and the mass of agents in each labor market state. Use these quantities to compute the budget-balancing tax rates.
4. Guess the equilibrium interest rate r.
5. Use the first-order conditions of the firm to compute the equilibrium wage w.
6. Use the endogenous grid point method to solve the optimization problem of working-age individuals and retirees.
7. Use the eigenvector method to solve for the cross-sectional distribution Φ.
8. Compute the implied equilibrium aggregate capital stock and the interest rate r'.
9. If r' is sufficiently close to r, stop. Otherwise, update r using the bisection algorithm and continue with step 5.

We use the Tauchen-method with three grid points and the Rouwenhorst-method with 7 grid points to discretize, respectively, the transitory component and the permanent component of the stochastic productivity process. Together with the three labor market states and the retirement state, this yields a Markov chain with $7 \times 3 \times 3 + 1 = 64$ states. In the endogenous grid point method, we use a grid for assets with 301 exponentially spaced points to cover the range $[0, 10, 000]$. When computing the stationary distribution Φ, we interpolate the policy functions linearly on a finer grid of 1,000 points. In the last step of the iteration, we extent this grid to 5,000 points. Note that we exploit the sparsity of the transition matrix to speed up the code, as we need to repeatedly solve for the largest eigenvector of a $192, 000 \times 192, 000$ or $320, 000 \times 320, 000$ matrix for each h-type.

K Growth of Earnings, household Income and Household Consumption

K.1 Actual Growth

For the calculations, we use observations on household heads (aged 25-60 years) taken from the SRC sample of the 2013-2019 waves of the PSID. Our measure of consumption expenditures comprises of the annual household expenditures on all expenditure categories reported in the PSID. This includes expenditures on food (variable code in the 2019-wave: ER77513), housing (ER77520), transportation (ER77539), education (ER77562), child care (ER77564), health care (ER77566), clothing (ER77581), vacation trips (ER77583), and recreation (ER77585). Total household income (ER77448) includes the annual taxable income, transfers and social security receipts of all family members. Earnings (ER77315) consist of the head's annual wage and salary income, as well as bonuses, overtime payments, tips, commissions and other labor income (but not farm income and the labor portion of business income). We follow Guvenen (2009) and exclude observations of earnings for which the reported annual hours (ER77255) are below 520 (10h/week), or above 5110 (14h/day), and the implied hourly wage is below half of the federal minimum wage rate of 7.25$.

All nominal variables are deflated by the CPI (CPIAUCSL) taken from the FRED database of the Federal Reserve Bank of St. Louis. Household income and expenditures are converted into per-capita terms by applying a standard equivalence scale. According to this scale, the total effective number of household members is given by the weighted sum of adult household members and children, where the first household member aged 14 years and over is assigned a weight of 1, each additional household member aged 14 years and over is assigned a weight 0.5, and each child who is under 14 years old is assigned a weight of 0.3. As before, we define low-skilled individuals as those with 0-12 grades of school completed, middle-skilled as those with at least a high-school degree but no college degree, and high-skilled as those with at least a college degree.

To correct for outliers, we trim the data by excluding observations for which the level (growth rate) of earnings, income, or expenditures is above the 90^{th} (95^{th}) percentile and below the 10^{th} (5^{th}) percentile of the distribution of the respective variable. Moreover, we exclude observations with negative reported income, earnings or expenditures. We convert the 2-year growth rate of earnings, income and expenditures into annual growth (for income and expenditures) using the formula $(1 + g_{2y})^{\frac{1}{2}} - 1$, and into 4-months growth (for earnings) using $(1 + g_{2y})^{\frac{1}{6}} - 1$.

Lastly, we use sample weights to compute average growth rates.

K.2 Expected Growth

To compute the expected growth rates in the SCE, we use our baseline sample but do not impose that the expectations regarding labor market transitions are reported. This allows us to also include the answer to the monthly core survey at times where the Labor Market Module is not available. Additionally, in the baseline sample we rely on the Labor Market Module to assign non-employed workers to U or N. Hence, we collapse all non-employed workers (but with non-missing information) into a single group. Every month, individuals are asked about their expected annual earnings growth conditional that they keep their current job (Q23v2part2), about their expected annual growth of household income (Q25v2part2), and about their expected annual growth of household consumption expenditure (Q26v2part2). To compute the expected 4 months growth rate regarding annual earnings, we use question L3 (OO2e2) asking currently employed respondents about their current (expected annual earnings in 4 months). Contrary to the questions before, the latter two are part of the Labor Market Module.

All these nominal growth rates are deflated using the reported inflation expectations (Q9): To do so, we follow Armantier et al. (2016) and use the provided estimated mean based on the assigned probabilities to each bin of potential future inflation rates. For the 4 month growth rate, we compute the implied 4 month expected inflation rate using the previous formula. Then, we compute the median inflation rate for each considered group and for each variable separately to account for the fact that not all respondents see or answer all questions.

We further restrict the sample and exclude employed respondents earnings less than 15,080 USD. Additionally, to be able to deflate all expected growth rates, we require individuals to state their expected inflation rate. Finally, to account for outliers, we consider only those observations which fall into the 10^{th} (5^{th}) and 90^{th} (95^{th}) percentile for each variable, conditional on having answered it.

Lastly, we then estimate the means and medians of the deflated variables. In this step, as well as when we compute the median inflation expectation, we use sample weights. Similar to our baseline procedure, we re-weight the weights supplied by the SCE to match the share of each age and education cell in each labor market state of the corresponding sample from which the actual growth rates are computed.

L Model with Endogenous Labor Supply

In Section 4.5, we extend the baseline model by introducing an endogenous labor supply choice of employed individuals. This modification affects the following parts of the baseline model.

Preferences and assets:
We assume that each period individuals have one unit of disposable time, which they can allocate to working and leisure. Preferences are described by a CRRA utility function over current consumption and leisure:

$$u(c, \bar{l} - l) = \frac{c^{1-\sigma_c} - 1}{1 - \sigma_c} + A\frac{(1-l)^{1-\sigma_l} - 1}{1 - \sigma_l}$$

where $1 - l$ is leisure, and $\sigma_c, \sigma_l > 0$, $A > 0$.

Optimization problem of the working-age individual:
A working-age individual with assets a, human capital h, labor market state s, and productivity z, chooses consumption, labor l, and next period's assets to solve:

$$\begin{aligned} W_W(a,h,s,z) = \max\nolimits_{c,a',l} u(c, 1-l) \quad & +\beta\theta \textstyle\sum_{s'}\sum_{z'} \widehat{p}_h(s'|s)\pi_h(z'|z)W_W(a',h,s',z') \\ & +\beta(1-\theta)W_R(a',h) \end{aligned} \tag{2.1}$$

subject to

$$c + a' = (1 + r - \delta)a + y(a,h,s,z) \qquad \text{and} \qquad a' \geq \underline{a} \qquad \text{and} \qquad 0 \leq l \leq 1$$

Let by $l(a,h,z)$ denote the optimal policy function for labor. Earnings, y, depend on the individual's labor market state:

$$y(a,h,s,z) = \begin{cases} (1 - \tau - \tau_{ss}) \cdot w \cdot z \cdot h \cdot l(a,h,z) & s = \text{employed} \\ (1-\tau) \cdot b(h,z) & s = \text{unemployed} \\ T & s = \text{not in the labor force} \end{cases}$$

When employed, a worker with human capital h and productivity z earns $z \cdot h \cdot w \cdot l$, where w is the wage per efficiency unit of labor and $z \cdot h \cdot l$ is the worker's labor supply in efficiency units. Unemployed workers receive benefits $b(h,z)$, which are a constant fraction ρ^u of the individual's potential wage earnings, that is given by $b(h,z) = \rho^u z \cdot h \cdot w \cdot \bar{l}$, where $\bar{l}(h,z)$ is the average labor supply by individuals with (h,z). Individuals who are not in the labor force receive welfare transfers, denoted by T. We model T as a constant fraction $\rho^n \in [0,1]$ of average labor earnings per worker in the economy. Average labor earnings are computed as $\frac{\int wzhl(a,h,z)\mathbb{1}s=ed\Phi(a,h,z,s)}{\int \mathbb{1}s=ed\Phi(a,h,z,s)}$, which is the wage per efficiency unit of labor times the efficiency labor per employed worker.

Budget constraints of the government and the social security program:

$$\tau \int wzhl(a,h,z)\mathbb{1}s = e + b(h,z)\mathbb{1}s = ud\Phi(a,h,z,s) = \underbrace{\int b(h,z)\mathbb{1}s = ud\Phi(a,h,z,s)}_{\text{Unemployment benefits}} + \underbrace{\int T\mathbb{1}s = nd\Phi(a,h,z,s)}_{\text{Welfare benefits}} \tag{2.2}$$

$$\int b_{ss}(h)\mathbb{1}s = rd\Phi(a,h,z,s) = \tau_{ss} \int wzhl(a,h,z)\mathbb{1}_{s=e}d\Phi(a,h,z,s) \tag{2.3}$$

In the calibration, we follow Marcet et al. (2007) and set $A = 2$ and $\sigma_c = \sigma_l = 1$. All other parameters and stochastic processes are as in the baseline model.

Chapter 3

Non-Convergence of East German Wages: Effects of Skill Shortage on Firm Organization

1 Introduction

In 2020, three decades after reunification, average labor productivity and real wages were still over 20% lower in East Germany than in West Germany. Over the years, a rich literature has developed trying to explain the causes of this phenomenon. While the focus has centered around the role of firms, highlighting especially the absence of large firms in East Germany, it remains an open question why East Germany has not yet fully caught up with West Germany despite featuring the same legal framework.

Induced by heterogeneity in the education system across the federal states –the major aspect where the legal setting does differ in Germany– I document that the share of high-skilled (i.e., highly educated) workers developed very differently across the regions in the past three decade alongside the non-convergence of productivity and wages. While both regions saw a strong increase in the share of high-skilled workers, the gap widened in favor of West Germany leading to a 40% lower share in East Germany in 2017.

Motivated by these patterns, this paper proposes and quantifies a new explanation for the gaps in productivity and wages between East and West Germany. With firms hiring non-homogeneous labor inputs and adjusting the organization of their production process as emphasized in the firm organization literature (e.g., by Caliendo et al. (2015)), the relative scarcity of high-skilled workers leads East German firms to operate under a different organization of production, i.e., with a shifted within-firm skill distribution, than their West German counterparts. If the different organization, as argued in this paper, leads to smaller, less productive, lower paying firms in the cross-section, the lower relative labor supply of high-skilled workers will not only contribute to the observed lower wages of low-skilled workers themselves, but will also affect high-skilled workers, as well as productivity in East Germany. To gauge the importance of this channel, the paper is organized into two parts.

In the first part, I perform an empirical analysis to obtain stylized facts about the relationship between wages, within-firm composition, and firm size by exploiting two rich administrative datasets: the Sample of Integrated Labour Market Biographies (SIAB) and the Sample of Integrated Employer-Employee Data (SIEED).

Using the long-established SIAB, which is representative for workers, I document wage patterns for low- and high-skilled workers over time. First regarding average wages by skill, the skill premium is lower in West Germany in line with the larger share of high-skilled workers in West Germany. Moreover, the large aggregate wage gap is mirrored by the wage gap of the two skill groups. A decomposition of the aggregate wage gap shows that the wage gap of low-skilled workers contributes the most due to the higher number of low-skilled workers in combination with the larger relative gap. Second, as these calculations neglect compositional effects on the worker and firm side, I consider the marginal effect of working in each region controlling for observables. While preserving the stability of the regional wage gaps over time, accounting for compositional differences reduces their levels. In particular, differences in the composition of firms contribute over 40% of the unconditional gap for high-skilled workers. For low-skilled workers, only 27% of the wage gap can be attributed to different compositions, emphasizing the question about the origin of wage differentials for this group of workers and their relation to the supply of high-skilled workers. Accounting for compositional differences in the decomposition leads to a small direct effect of a lower high-skilled share of less than two percentage points.

Following up on the importance of establishment characteristics[1] for high-skilled wages, I use the SIEED to analyze the relationship between the workforce composition of an establishment, its size as well as the wages paid to each worker type. This is possible since the recently published SIEED provides information on the whole workforce of sampled establishments and is representative at the establishment level. I find a positive relationship between the size and the share of high-skilled workers in an establishment, as well as positive semi-elasticities regarding wages for both worker types and regions controlling for observables including firm size. This is in particular true for low-skilled in East Germany with an estimated coefficient of 0.472 implying a 8.6% higher wage when working for a firm with a one standard deviation higher share of high-skilled workers. Repeating the exercise on a yearly frequency, the regression implies an up to 7% higher wage for low-skilled workers in East Germany in a counterfactual world, where East Germany has the same aggregate workforce composition as West Germany. This indicates a more important role for the lower relative

[1]While the datasets do not allow to link establishments to firms, I use the terms establishments, firms, and plants interchangeably.

labor supply as suggested by the small mechanical effect when considering additional effects operating via the firm side. Naturally, since the firm distribution is endogenous, to estimate effects on productivity and to be able to perform counterfactual experiments, I use these results as input to a structural model.

In the second part, I utilize a general equilibrium model, informed by the empirical part, to quantify the effects of the smaller relative supply of high-skilled workers in East Germany on the firm distribution, on wages as well as on productivity. At its heart, frictions in the labor market are responsible for differences in wages across firms and regions. The model builds on Kaas and Kircher (2015) which provides a tractable framework in the presence of large firms operating in a frictional labor market. In the model, firms face convex vacancy posting costs, leading to a trade-off between offering higher wages to attract more applicants or to post more vacancies. As a consequence, the model features wage heterogeneity across firms with different growth rates, age and size.

I extend the baseline model in two main dimensions: First, to mirror the empirical analysis, I introduce ex-ante worker heterogeneity in the form of low and high-skilled workers. These workers differ in terms of their productivity as well as in their labor market transition rates, and are both needed in the production process of firms. The complementarity across worker types in the production function is motivated by the positive relationship between wages for low-skilled workers and the skill composition within firms. Second, I include an additional dimension of heterogeneity on the firm side which I label the *firm type*. Firm types differ in their production function and in their vacancy posting cost function. This generates (additional) heterogeneity in the composition of the workforce among firms and provides tractability as the model stays block-recursive. The model replicates the positive wage-share relationship as the firm type with a higher output elasticity of high-skilled workers, employs relatively more of these workers and pays higher wages economizing on vacancy costs. Moreover, I keep the model tractable in the presence of rich heterogeneity by imposing two assumptions. First, I assume that workers do not endogenously choose their educational attainment based on their employment prospects as educational choice is outside of the scope of this paper. Second, I make the strong assumption that the two labor markets are completely separated such that workers cannot transition between the two regions. While this limiting case of spatial frictions is clearly not observed in reality, the empirical section provides evidence that migration between East and West Germany played only a minor role regarding differences in the relative supply of high-skilled workers. Together, the two assumptions imply that the relative supply of workers in each region is exogenous, simplifying the model considerably.

The model is calibrated to East Germany in 2015 and the experiment increases the relative supply of high-skilled workers to the West German level. Keeping all other variables fixed at their calibrated values, the experiment compares the firm distribution, wages, and productivity of this counterfactual scenario to West Germany. In the experiment, the firm distribution shifts towards larger firms, and the elasticity of wages with respect to the high-skilled share decreases in line with the data. Most importantly, the model implies that 26% of the wage gap after controlling for worker and job characteristics between East and West Germany can be explained by the different relative supply of workers. For the wage gaps conditional on worker skill, this number changes to about 25% for low-skilled and over 5% for high-skilled worker, highlighting the importance of high-skilled workers for low-skilled wages. Finally, the model predicts output to increase by over 5% which would close the aggregate productivity gap by approximately 20%.

Related Literature This paper is related to various strands of the literature. First, the paper contributes to the literature studying wage and productivity differences within Germany. While this literature saw continued contributions over the last decades (see Burda (2006), Uhlig (2006), Fuchs-Schündeln and Izem (2012) among others), newly available micro datasets spurred new interest. Focusing on the years directly following the German Reunification, Findeisen et al. (2021) find that the reallocation of workers across firms within East Germany, in particular the shrinking of large firms, was an important factor for the fast, initial growth of East German wages. In a similar spirit, Heise and Porzio (2022) study the impact of spatial and labor market frictions on the misallocation of labor across firms and regions. They find that productivity differences are the major driver of lower wages in East Germany, but differences across workers ("home location") also contribute substantially. Bachmann et al. (2022) emphasize the different plant size distribution in combination with a different size-wage relationship across the regions, and use a model about plant entry and consumer accumulation to explain the lower productivity in East Germany. My paper complements this strand of the literature. In contrast to Heise and Porzio (2022), worker types in my model differ by skill instead of home location. Together with additional heterogeneity on the firm side and complementarities across workers and firms, this leads to a more detailed firm distribution where the workforce composition matters, at the cost of the rich spatial structure. Compared to Bachmann et al. (2022), instead of a reduced form size-wage relationship, my model features labor market frictions and richer worker heterogeneity which allow to look at the effects of workforce composition within firms in addition to the size of firms. Methodologically, in particular regarding the experiment, the paper is closest to Bachmann et al. (2022), which also analyzes the two regions in the model in isolation.

Second, the paper is related to the literature studying the effect of factor misallocation on aggregate productivity in general (e.g., Hsieh and Klenow (2009)), and the effects of labor market frictions in particular (e.g, Bilal et al. (2021), Elsby and Gottfries (2022) and Heise and Porzio (2022)). It also relates to Grobovšek (2020) which studies the effect of law enforcement on the internal organization of firms and in turn on aggregate productivity. The paper contributes to this literature by combining these two directions and studying the effects of labor market frictions in the presence of heterogeneity in the organization of firms.

Third, regarding the empirical results, the paper is related to three different strands of the literature. The first strand concerned with explaining productivity differences across firms, looks at the workforce composition within firms (see Doms et al. (1997) and Haltiwanger et al. (1999) for early influential contributions) estimating positive correlations between the skill distribution of firms and proxies for firm productivity like the use of advanced technologies (Abowd et al., 2007) or firm size (Antonelli et al., 2010), among others. The second strand analyzes the effects of trade liberalization on wage inequality and the skill premium which was strongly influenced by the findings of Bernard and Jensen (1997) that the observed increase in relative demand for skilled labor in manufacturing during the 1980s was mainly driven by the increase in employment at exporting plants. This literature finds that the wage effects of exporting depend positively on the skill composition (Munch and Skaksen, 2008) and that exporters are larger and more skill intensive than non-exporters (Bernard et al., 2007). Augmenting the Melitz (2003) model with firm heterogeneity in skill intensity, Harrigan and Reshef (2015) provides a theory that predicts that trade liberalization leads to an increase in the relative demand for skill and greater trade volumes as the most productive, most skilled firms expand. While not considering the exporting status of firms, both strands are in line with my empirical findings that large firms are, on average, more skill intensive, and that they pay higher wages to both types of workers. Additionally, by nature of regarding the relative labor supply of low and high-skilled workers and their wages, the paper is related to the literature concerned with skill biased technical change (see, e.g., Acemoglu (2002) and Violante (2008)). However, I do not consider a change of technology over time and focus on the role of firms. Finally, the empirical (and model) results are related to Eppelsheimer and Möller (2019). They find that inflows of high-skilled workers generate positive externalities on wages as predicted by the size-share regression and the experiment in this paper.

Fourth, in terms of the model, I mainly build on Kaas and Kircher (2015) which introduced large, slow growing firms in a model with directed search. Compared to other papers in this literature like Schaal (2017) and Eeckhout and Kircher (2018), vacancy costs are non-linear, implying that firms do not directly jump to their optimal level of employment. In the presence of worker heterogeneity, this implies an additional source for differences in the composition of the workforce within firms. I am not the first to introduce worker heterogeneity in the framework of Kaas and Kircher (2015). Mueller et al. (2022) extend the model with two worker types to study the relationship between the duration of a vacancy and the starting wage. However, they assume that there are no interactions between different worker types within the firm, i.e., output and vacancy costs are additively separable. This effectively means that in terms of wages and output, their framework is observationally equivalent to a setting where two different firm types hire only a single worker type, hence leaving no room for the organization of the firm to affect productivity. This is in contrast to a growing literature emphasizing worker complementarities during the production process (see, e.g., Herkenhoff et al. (2018) and Jarosch et al. (2021)). In this regard, my model relates to Cahuc et al. (2008), Eeckhout and Pinheiro (2014), and Caliendo et al. (2015) among others that study the organization of firms.

Outline The remainder of the paper is structured as follows. In the next section, I describe the datasets and define worker skill. Section 3 contains the empirical analysis. In Section 4, the model is laid out. Section 5 discusses the calibration of the model and Section 6 presents the model fit as well as the results of the model. The main experiment is conducted in Section 7. Section 8 concludes.

2 Data

For the empirical analysis and to calibrate the model, I exploit three administrative datasets: the Sample of Integrated Labour Market Biographies (SIAB) 1975-2019, the Sample of Integrated Employer-Employee Data (SIEED) 1975-2018, and the Establishment History Panel (BHP) 1975-2019.[2] All datasets are provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and were accessed on-site at the FDZ and remotely.

The datasets share the Integrated Employment Biographies (IEB) as their basis, but differ in their sampling strategy and in the available pieces of information. The IEB contains, among others, the universe of all employment spells subject to social insurance, all unemployment spells eligible for unemployment benefits as well as all registered job seekers at the Federal Employment Agency. Therefore, the IEB captures the whole German labor market except for employed workers not subject to social insurance like self-employed and civil servants. Depending on the year, it accounts for 66% to 75% of total employment in Germany according to the BA.

For individuals, the IEB comprises information on gender, year of birth, the federal state of the residence, vocational training, and school leaving qualification. For establishments, the industry, the date of the first and last appearance, as well as the federal state of the workplace are available. Additionally, aggregated worker information on the establishment level, like the number of full-time worker are included.[3] Most importantly, the IEB contains daily information about the labor market status of each individual, details about the occupation, as well as the average daily[4] wage[5] or benefit over the horizon of the spell.

The next three sections describe the sample selection and the datasets in detail. Section 2.4 explains the definition of the skill groups used throughout the paper.

[2] To be precise, the datasets are the weakly anonymous Version of the Sample of Integrated Labour Market, Biographies (SIAB) – Version 7519 v1, the Sample of Integrated Employer-Employee Data(SIEED) – Version 7518 v1, and the weakly anonymous version of the Establishment History Panel – Version 7519 v2.

[3] For the complete list see Frodermann et al. (2021). Some variable like the location of the residence or workplace are available on a less aggregated level but only accessible upon special request.

[4] Since establishments have to issue a notification not only if a worker starts or ends working, but also at the end of each year, the reported daily wage represents at worst an average over the whole year.

[5] Gross daily wages are reported in Euro and are top-coded due to employers only having to report earnings up to the (time- and region-varying) upper earnings limit for the statutory pension insurance. For example, this limit was 190.68€ (213.70€) per day in East (West) Germany in 2018. To gauge the impact of the top-coding, I perform robustness exercises without any top-coded wages and with imputed wages using the procedure of Dauth and Eppelsheimer (2020) based on Card et al. (2013).

2.1 Sample of Integrated Labour Market Biographies (SIAB)

The Sample of Integrated Labour Market Biographies constitutes a 2% random sample of all individuals with at least one entry in the Integrated Employment Biographies between 1975 and 2019. This implies that the SIAB is representative for employed and job-seeking individuals in the German labor market excluding those not subject to social insurance.[6] In addition to the pieces of information described earlier, the SIAB is enriched by variables describing total employment and averages wages for different subgroups within each establishment as well as by firm and worker fixed effects.[7]

Over the whole horizon, the SIAB contains over 1.9 million individuals with more than 51 million spells.[8] Therefore, the SIAB is best suited to analyze the evolution of the East and West German labor market since reunification on a worker level. In particular, I consider the time span from 1993 to 2017 as 1993 constitutes the first year for which the SIAB provides full information on the East German labor market. I do not use the last two years of the SIAB, as the data in the last three years are not finalized and might be updated in the future, and to stay consistent with the SIEED.[9]

Throughout the paper, I consider only (spells at) establishment in the non-primary, private sector following Bachmann et al. (2022). For the empirical analysis, I generate an annual dataset by regarding only the spells covering June 30 in each year –the date for which information about the establishments are available in the IEB– and selecting the main employment spell, i.e., the spell with the highest daily wage. Due to the absence of information on working hours, I restrict the sample further to only full-time working individuals without marginal employment. Additionally, I do not include workers in vocational training or employed by a temporary work agency. Finally, I consider individuals aged 16 to 60, with a strictly positive wage, and with information about their working region as well as their (imputed) educational background (see Section 2.4). As reported in Table 3.7 in Appendix A.1, these restrictions result in a sample with at least 231,000 observations per year in West Germany and 36,000 observations per year in East Germany.

2.2 Sample of Integrated Employer-Employee Data (SIEED)

For the Sample of Integrated Employer-Employee Data, a 1.5% random sample of all establishments with at least one entry in the Integrated Employment Biographies at the reference date of June 30 in a year between 1975 and 2018 is drawn. Therefore,

[6] Marginal part-time employment is recorded from 1999 onward.

[7] The so-called AKM fixed effects due to Abowd et al. (1999) are described in Bellmann et al. (2020).

[8] See Frodermann et al. (2021) for further information about the dataset and the sampling procedure.

[9] Note that 2016 is the last year containing the final version of the IEB dataset. For 2017 and 2018, a preliminary version of the IEB subject to delayed reports is used. However, as all reports from the succeeding 18 months (instead of the usual 36 months) are included, the missing spells for 2017 should be sufficiently small.

the SIEED is representative for German establishments.[10] For all employees working at least for one day at one of these establishments, all employment spells between 1975 and 2018 are available. This implies that for sampled establishments the entire workforce and the wage structure is observable in the dataset over the whole horizon. Additionally, also the wages and establishments before and after working at one of the sampled establishments are in the dataset. However, for these establishments, it is not guaranteed that all employees are observed, and will be excluded in the main sample. Except for the different sampling strategy, the SIEED contains the same basic variables as the SIAB which are described in the previous section.[11]

The raw dataset contains over 5.2 million establishments (with and without full information about the workforce) and over 5.5 million individuals with more than 157 million individual spells. Mirroring the procedure applied to the SIAB, I consider the years 1993 to 2017[12] after the German Reunification and apply the same sample restrictions. After cleaning, the dataset contains at least 14,300 (2,700) sampled establishments with a combined workforce of at least 186,000 (28,000) per year for West (East) Germany.

2.3 Establishment History Panel (BHP)

The Establishment History Panel represents a 50% random sample of all establishments with at least one entry in the Integrated Employment Biographies at the reference date of June 30 between 1975 and 2019. For sampled establishments, all years where the establishment employs at least one worker subject to social security are included. To allow for a total of over 3.3 million establishments, only establishment characteristics and worker information aggregated to the establishment level like the number of workers of different groups (e.g., by gender or vocational degree) and their average wage are available. Moreover, the extension file ”entry and exit” is used which provides additional information on the type of establishment entry and exit using the method described in Hethey and Schmieder (2010).

As described in Section 2.1, I restrict the sample to the years between 1975 and 2017 and to establishments in the private, non-primary sector. The final dataset contains 615,000 (124,000) establishments in West (East) Germany in 1993 with more establishments entering the sample each year. Table 3.7 reports the number of establishments in each year and region.

[10] The datasets do not allow to link establishments to firms.

[11] See Schmidtlein et al. (2020) for further information about the dataset and the sampling procedure.

[12] One year earlier than in the SIAB, 2015 is the last year containing all employment spells from the IEB. In the following years, the degree of underreporting is increasing. Hence, especially for 2018, not all employees in a given establishment can be observed.

2.4 Worker Skill

Throughout the paper, I refer to workers having different levels of *skill*. The level of skill an employee possesses is based on the highest educational degree at the start of the employment spell. Since information about educational and vocational attainments are not relevant for social insurance, the share of missing values for the educational variable in my main sample of the SIAB is relatively high and increases over time reaching about 45% after the change in occupational codes in 2011 and settling at around 20% to 25% in the subsequent years (see Frodermann et al. (2021) for a discussion of this issue). Furthermore, as establishments do not always update the reports as soon as an employee obtains a new degree or completes a training program, job movements are often accompanied by a change in the educational variable. Finally, education is not consistently coded over time, with education groups being merged and separated with the introduction of the new occupation classification system in 2011.

To alleviate these issues, I impute the school leaving qualification of a worker, *schule*, similar to Thomsen et al. (2018): First, I harmonize the variable over time classifying everyone without an entrance qualification for University (or University of Applied Sciences, FH) –usually a high-school degree– to be low-skilled and everyone with such an qualification as being high-skilled. Second, for all workers with only low-skill (high-skill) spells, I set the spells with missing education values to be low-skill (high-skill). Since all workers in my sample are at least 16 years old and full-time employed, I expect that the majority of workers with high-school degrees have completed school already at the point of entering the sample. Third, for workers with low-skill as well as high-skill observations, I write the qualification levels forward until a new level is reached. This is done only for the subset of workers which have monotonically increasing levels of skill. I do not impute any spells for workers with decreasing levels of skill.[13] With this imputation strategy, I reduce the number of missing observations to less than 8% per year in each region and skill group. Figure 3.17 in Appendix A.2 shows the share of missing observations for East and West Germany before and after the imputation procedure.

[13] Thomsen et al. (2018) imputes a combination of vocational and educational variables, while I only impute the level of education. Furthermore, they impose monotonicity by writing the level of qualification forward until a new level is reached. However, many workers are classified to be highly qualified in the beginning of their employment biographies with subsequent missing and low qualification periods. These spells are on average also associated with a very low wage. Therefore, I do not follow their monotonicity assumption.

3 Empirical Analysis

This section contains the main empirical analysis. Section 3.1 presents the well-known puzzle of non-converging productivity and wages between East and West Germany. Section 3.2 introduces differences in the education systems and documents the divergence in the share of high-skilled workers. Wage differences between skill groups are analyzed in Section 3.3. Finally, Section 3.4 considers the workforce composition within firms and their relation to wages.

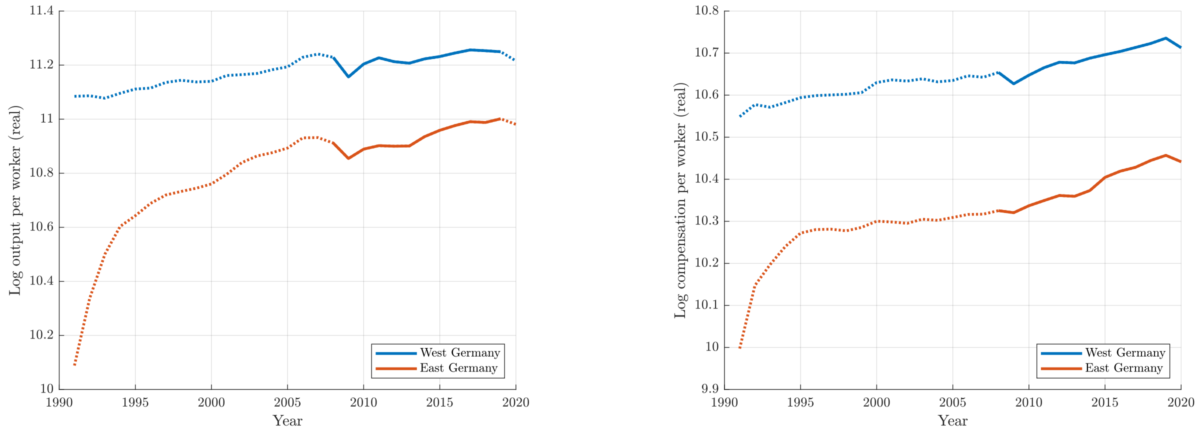
3.1 Aggregate Productivity and Wages

To set the stage for the remainder of the paper, Figure 3.1 –adapting the first plot in Bachmann et al. (2022)– compares the development of average labor productivity (Panel 3.1a) and yearly compensation (Panel 3.1b) per worker between East and West Germany over time.[14] As the figure shows, East German labor productivity and wages were under 60% and 40% of their West German counterparts, respectively, one year after the reunification, but started to catch up quickly in the following four years. By 1995, one third of the original wage gap was already closed. However, in the subsequent years, the East German convergence came to a complete halt as labor productivity and average wages started to feature very similar dynamics for both regions. Consequently, the differences remained stable from 1995 to 2014. In the recent years, the gaps started to shrink again, but by 2020 –three decades after the reunification– East Germany still featured a 23% lower labor productivity and 20% lower wages than West Germany.

3.2 High-Skilled Worker Share

The non-convergence of productivity and wages of the previous section is especially puzzling in the light that East and West Germany feature the same legal system. However, while the legal framework and many labor market institutions are the same, one important source for legal differences across the federate states (*states* in the following) is their constitutionally guaranteed responsibility for culture in general, and for education in particular.[15] After the Second World War and the adoption of the constitution, the states in West Germany re-instated different education systems. In contrast, the education system in East Germany was centrally governed during the existence of the German Democratic Republic (GDR). After the German Reunification, the East German states gained control over the education system, and had to drastically re-design the curriculum as well as the whole system itself (see Fuchs-Schündeln

[14]See Bachmann et al. (2022) for statistics regarding working hours and the whole economy.
[15]Article 30 and Article 70 par. 1 GG



(a) Output per worker

(b) Compensation per worker

Figure 3.1: The figure shows average yearly output and average yearly compensation per worker for East and West Germany over time. The connected line represents the private, non-primary sector, while the dotted line also includes the mining sector. Average output per worker is measured as log(gross value added/number of worker). All numbers are deflated.[16] Source: national accounts (VGR)

and Masella (2016)). This development over time led to very heterogeneous education systems across Germany.

While it is not the goal of the paper to evaluate education systems, these differences have important implications for the labor force composition in the regions.[17] As Figure 3.21d in Appendix A.6 shows, the participation rates in the education system among 15 to 19 years old in East German states are the lowest among all states for both 2004 and 2019. In combination with the older age structure in East Germany, this implies that the population share of students is lower in East Germany than West Germany as visible in Figure 3.21b.[18]

As depicted in Figure 3.2, this relative lack of students over time is reflected in a lower share of high-skilled (full-time employed) workers (i.e., workers with an entrance qualification for university as defined in Section 2.4) in East Germany compared to West Germany.[19] Moreover, the figure shows that at the same time of the non-convergence of productivity and wages, the share of high-skilled workers has

[16] Throughout the paper, I use the procedure from Bachmann et al. (2022) to deflate prices in each region: Using county-level consumer price indices taking into account housing, goods, and services for 2016 from Weinand and von Auer (2020), I compute an aggregated price index for East and West Germany, weighting each county with its population. Then, setting 2016 as the base year, I use the deflated time series of regional GDP from national accounts (VGR), to generate price indices for each year of the sample.

[17] In line with the skill definition from Section 2.4, I focus on primary and secondary education.

[18] Despite East German states having higher expenditures per student (Figure 3.21), this leads expenditure over population (Figure 3.21c) to be higher in West Germany after being lower before 2002.

[19] Figure 3.18 in Appendix A.3 compares the skill share among workers to the skill share for all employed and unemployed individuals in the SIAB. Due to the small differences and the fact that the SIEED only contains employment spells, I focus on the high-skilled share among the employed.

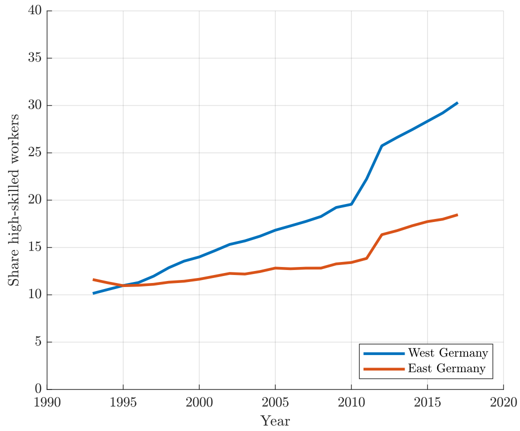


Figure 3.2: This figure depicts the share of high-skilled workers for East and West Germany over time. High-skilled workers are defined to have at least a high-school degree. See Section 2.4 for more details. Data source: SIAB

diverged. Four years after reunification, the high-skill share was very similar for East and West Germany. While it rose by nearly 0.6 percentage points on average each year in West Germany until 2010, the growth rate was less than a third (0.16 p.p.) in East Germany. Hence, by 2010, West Germany featured a 6 percentage point higher share than East Germany. 2011 and 2012 are less reliable for the skill measure as discussed in Section 2.4 due to the change in the classification system of occupations and associated changes. In the dataset, these years imply a sharp increase in the high-skilled worker share in both regions. After 2012, the growth rates are again constant in both regions and comparable to the earlier period. In 2017, the latest year of the sample, the high-skilled worker share was about 18.5% in East Germany – 40% lower than the share in West Germany.[20]

One alternative explanation for the differential change in the high-skilled share across the two regions are migration flows. Despite considerable gross flows between East and West Germany, migration however only contributes up to 10% of the gap in the share of high-skilled workers as discussed in Appendix A.5. Therefore, the majority of the divergence is driven by changes in the composition of workers within each region. This is consistent with the aforementioned patterns: a decrease (increase) in the participation rate of young workers in the education system in East (West) Germany, a resulting increase (decrease) in the share of people with a secondary school degree in East (West) Germany, and an older population in East Germany. Together with the larger skill premium documented in the next section and the stronger increase in the employment-to-population ratio by education in East Germany shown in Table 3.8 in Appendix A.7, I interpret this larger share of high-skilled workers as

[20]Appendix A.4 verifies the robustness of this trend regarding the imputation procedure and variable choice, and shows that the trend is confirmed by the Microcensus using a different sample.

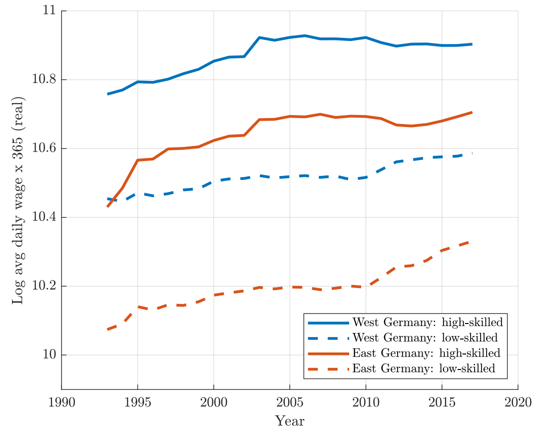


Figure 3.3: The figure shows the implied yearly log wages by skill group for East and West Germany. All numbers are deflated. Data source: SIAB

supply driven as opposed to originating from differential firm demand across the regions.

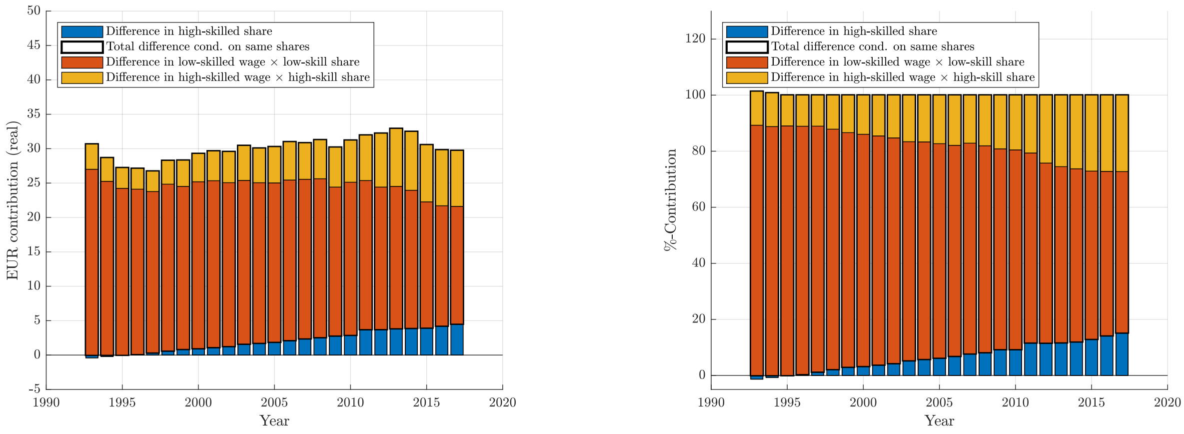
After having documenting the higher and diverging relative supply of workers in West Germany compared to East Germany, the next section focuses on the wages for the different groups of workers.

3.3 Wage Heterogeneity

In the light of the different trends in relative labor supply between East and West Germany, I shift my attention from aggregate wage differences to wage developments by worker skill. The main objectives of this section are to quantify the contribution of each skill group regarding the aggregate wage gap and to analyze the wage patterns over time. In particular, the question is whether the stability of the aggregate wage gap is driven by opposing forces for each group or whether the non-convergence of wages of the aggregate level applies to the individual groups as well.

To answer these questions, I turn to the SIAB.[21] I first consider again average wages but slice the sample by worker skill. Figure 3.3 shows implied yearly average wages for each skill group and region. As the figure presents remarkable clearly, the non-convergence of average wages between East and West Germany applies to average wages for each skill group, too. Additionally, the figure allows for a comparison between the wage gaps of the two skill groups. While absolute wage gaps are quite similar with a 28€ and a 30€ lower daily wage for low- and high-skilled workers in East Germany, respectively, the relative wage gap is significantly larger for low-skilled workers: the average wage for this group is about 27% lower in East Germany while high-skilled workers earn about 20% less. Finally, in line with the lower share of

[21] Figure 3.22 in Appendix A.8 compares averages wages in the SIAB to the ones obtained from national accounts and finds no differences exceeding those expected by the different sample construction.



(a) Absolute contribution

(b) Relative contribution

Figure 3.4: The figures decompose the difference in average real wages for East and West Germany into two main components: first, the difference in the share of high-skilled workers weighted by the skill premium in East Germany and, second, the difference due to the wage gaps of the skill groups weighted by the size of the groups in West Germany. Additionally, the last component is split into the contribution of each group separately by multiplying the corresponding wage gap with the relative size of the group. See equation (3.1) for details. Data source: SIAB

high-skilled workers in East Germany, the skill premium is higher in East Germany (a wage ratio of 1.45 compared to 1.37 in 2017), indicating that labor demand affects are not the main driver of the observed divergence in relative supply.

To gauge the importance of the differences in the size of each skill group (Figure 3.2) vis-à-vis their wage gaps (Figure 3.3) for the aggregate East-West German wage gap, I perform the following accounting exercise for each year:

$$\begin{aligned} \overline{w}^{\text{west}} - \overline{w}^{\text{east}} = s^{\text{west}} \left(\overline{w}^{\text{west}}_{\text{high}} - \overline{w}^{\text{east}}_{\text{high}} \right) + \left(1 - s^{\text{west}}\right) \left(\overline{w}^{\text{west}}_{\text{low}} - \overline{w}^{\text{east}}_{\text{low}} \right) \\ + \left(s^{\text{west}} - s^{\text{east}} \right) \left(\overline{w}^{\text{east}}_{\text{high}} - \overline{w}^{\text{east}}_{\text{low}} \right) \end{aligned} \tag{3.1}$$

where s denotes the share of high-skilled workers and $\overline{w}$ represents the average daily wage of the specified group. This yields a decomposition into three components: The first and second component measure the differences in average wages for high- and low-skilled workers fixing the share of high-skilled workers to the West German level. Together, these two terms measure the wage gap between East and West Germany, if both regions had the same, West German high-skilled share. The last component represents the contribution to the wage gap due to a smaller share of high-skilled workers in East Germany accounting for the East German skill premium.

Figure 3.4 displays the absolute and relative contribution of each of the three components over time. The figure presents two important implications of the documented stability of the wage gaps for the two worker groups: First, the strong rise in the share of high-skilled workers in West Germany implies that the contribution of high-skilled workers and their wage gap increased over time, from about 10% in 1995 to 27% in 2017. However, since the majority of workers in both regions are low-skilled, they contribute the most to differences in the average wage. Second, the contribution of the difference in the high-skill shares increases substantially over time, from about 0% in 1995 to 15% in 2017, as a direct consequence of the divergence in the share across the regions. Mechanically, this implies that the aggregate wage gap had been be 15% lower in 2017 and had changed by -7% instead of 9% compared to 1995, if East Germany would have seen the same growth in the share of high-skilled worker as West Germany.

While this contribution seems large at first glance, by its nature, this simple accounting exercises abstracts from any additional compositional differences across East and West Germany and endogenous reactions thereof in response to a change in the share of high-skilled workers. Whereas the quantitative model of Section 4 is used to study the effects operating through the firm side in detail, the remainder of the section takes differences in the composition of workers and firms more serious.

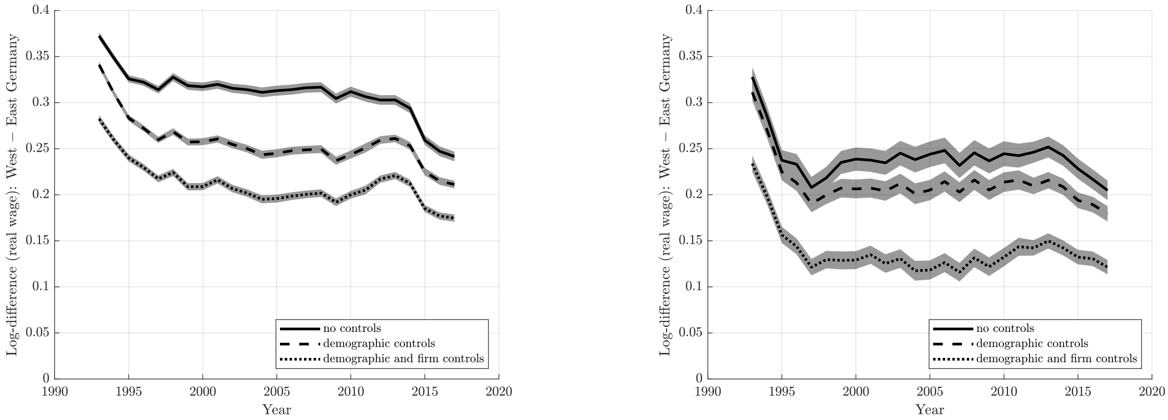
There are many potential reasons why compositional differences might lead to higher wages in West Germany than in East Germany. For example it might be that workers in West Germany are on average more experienced, therefore earning a higher wage. Moreover, a common explanation for wage differences between East and West Germany is the differential in firm characteristics, since establishments are smaller in East Germany, and firm size is positively associated with the wage level as documented in Bachmann et al. (2022).

To evaluate the importance of difference in the composition of workers and firms across the regions, I re-estimate the East-West German wage gap conditional on worker skills controlling for additional worker and firm-level observables. To do so, I estimate the following regression for each year

$$\log(w_{it}) = \alpha + \beta_w West_{it} + \beta_h High_{it} + \beta_{wh} West_{it} \times High_{it} + \gamma X_{it} + u_{it} \tag{3.2}$$

where *High* and *West* are binary variables indicating high-skilled workers and a workplace in West Germany, respectively. X can include additional worker characteristics in the form of age, age squared, and sets of dummy variables regarding gender, 3-digit occupations, and 12 different industries as well as firm age and log firm size depending on the specification.[22] The main interest lies in the β coefficients, since β_w ($\beta_w + \beta_{wh}$) measures the wage premium of working in West Germany for low-skilled (high-skilled) workers. I run the regression with three different specifications to estimate the impact of compositional differences: In the first specification, I use no

[22] Including six distinct levels measuring the vertically of jobs as motivated by Bayer and Kuhn (2019) has very little effect.



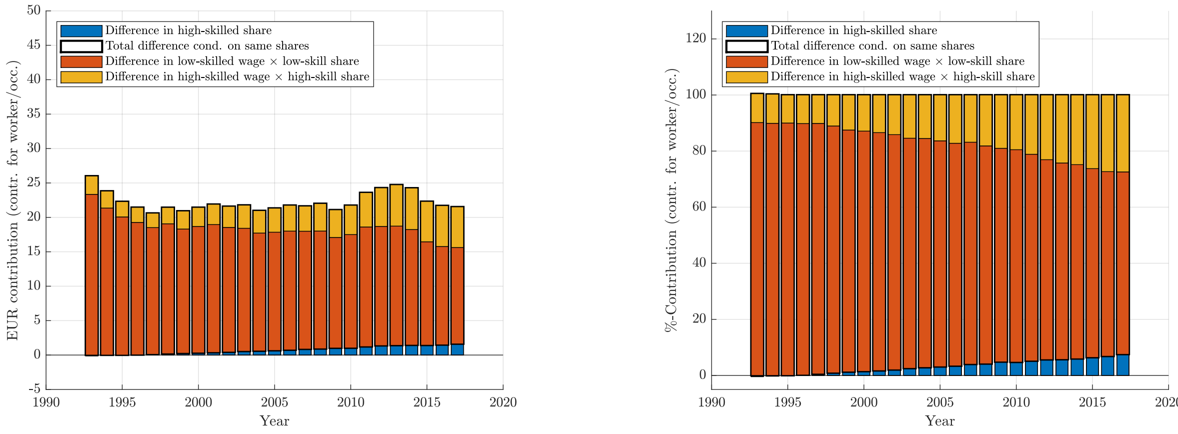
(a) Low-skilled **(b)** High-skilled

Figure 3.5: The two panels show the estimated East-West German wage gap for low-skilled (left panel) and for high skilled (right-panel) for three different specifications: unconditional, conditional on worker and job characteristics, and additionally conditional on firm characteristics. The gaps are defined as β_w and $\beta_w + \beta_{wh}$ from equation (3.2). The shaded areas represent the corresponding 95% confidence intervals. Data source: SIAB

additional controls (X is empty). In the second specification, X contains all variables listed above except firm age and size. The third specification features the full set of control variables.

Figure 3.5 plots the estimated wage gap for each specification and for each skill group (β_w and $\beta_w + \beta_{wh}$).[23] Focusing on the low-skilled in Panel 3.5a, the evolution of the wage gaps over time remains nearly unchanged when controlling for additional observables. In particular, the only years where the shape differs when controlling for worker and occupation characteristics are the ones corresponding to the change in the occupational classification system. From 2014 onward, these differences disappear. In contrast to the behavior over time, the level of the wage gap drops the more control variables are included, from around 36% for the unconditional case to around 29% and 23% when controlling for worker/occupation as well as worker/occupation/firm characteristics, respectively. This implies that about 35% of the relative gap for low-skilled workers are due to compositional differences in the included variables across East and West Germany. In other words, 65% of the 0.3 log-point difference for low-skilled workers are left unexplained. The wage gap for high-skilled workers behaves similarly as the one for low-skilled as shown in Panel 3.5b. Again, the patterns across the specifications differ the most for the years 2011 and 2012, and the wage gap declines in the number of included control variables. In contrast to Panel 3.5a, the unconditional level is lower, and the estimated gap drops stronger for the specification where firm characteristics are included –from 27% for the unconditional case to 24%

[23] Appendix A.12 shows the same plots excluding censored wages or imputed wages. While the level for high-skilled workers is slightly different, the overall patterns are the same.



(a) Absolute contribution

(b) Relative contribution

Figure 3.6: The figures decompose the difference in wages controlled for worker and occupation characteristics (equation 3.2) for East and West Germany into two main components replicating Figure 3.5. See equation (3.1) for details. Data source: SIAB

when controlling for worker and occupation characteristics to 15% for the specification with firm characteristics. In total, compositional differences account for around 45% of the observed unconditional wage gap for high-skilled workers. For the specification with worker and occupation controls, the skill premium in each region declines compared to before, but still features a higher skill premium in East Germany (wage ratio of 1.16 for East Germany and 1.12 for West Germany). Finally, the difference between the wage gaps across the two groups remains surprisingly similar at around ten percentage points for the unconditional case as well as when controlling for the full set of observables.

To gauge the contribution of the two skill groups accounting for compositional differences, Figure 3.6 repeats the previous decomposition, but instead of average wages considers the implied wages after controlling for worker and occupation characteristics from the previous regression. As the figure shows, the mechanical effect of a larger high-skilled share plays indeed a very minor role: in 2017 it accounts for less than 2 percentage points (7% of the gap). In contrast, the decomposition assigns a more important role than previously to the contribution of low-skilled workers.

In summary, more experienced workers and larger firms in West Germany, as well as other observed compositional differences account for an important share of around 40% of the relative wage gaps for both groups across the two regions. However, the wage gaps across all skill groups and specifications are very stable after 1995 implying that the non-convergence of wages for low- and high-skilled workers between East and West Germany is not driven by compositional effects along the included dimensions. Additionally, low-skilled workers feature a robustly higher relative wage gap, emphasizing their contribution in combination with their higher relative supply.

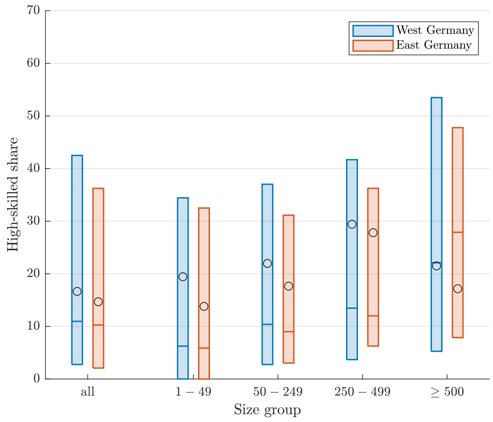


Figure 3.7: The figure shows the three quartiles and the mean of the employment weighted, within-firm high-skilled share distribution for different firm size groups in East and West Germany. While the box represents the quartiles, the circles indicate the mean of the distribution. To obtain sufficient observations for the largest size group, all years are pooled. Data source: SIEED

The implied mechanical effect from increasing the share of low-skilled workers in East Germany to the West German level while keeping all other factors like the firm distribution constant, implies a very minor effect.

3.4 Firm Organization

In light of the strong effects of firm-level variables on individual wages documented in the previous section, the questions of this section are: To what extent do firms in West Germany employ a different within-firm composition of workers, i.e., have a different organization of work, and to what extent does this explain the higher wages for low- and high-skilled workers in West Germany. In other words, are there additional effects of the higher relative supply of high-skilled workers operating via the firm side complementing the minor mechanical effect from the previous section? While the quantitative model from Section 4 will be used to study the effects in detail, this sections provides suggestive evidence by documenting differences in the firm share distribution across the regions and by comparing wages of workers in different firms along this distribution. To do so, this section exploits the SIEED which contains full information on the workforce of the sampled firm.

To start, the first set of bars in Figure 3.7 visualizes the 25%, 50%, and 75% quantile as well as the mean of the employment-weighted within-firm high-skilled share distribution for East and West Germany. In line with the higher average high-skilled share in West Germany implied by the SIAB, the average high-skilled share is also

	Low-skilled wage		High-skilled wage	
	West Germany	East Germany	West Germany	East Germany
High-skilled share	0.304 (0.001)	0.472 (0.001)	0.085 (0.017)	0.150 (0.004)
Log firm size	0.065 (0.0001)	0.069 (0.00009)	0.058 (0.00003)	0.085 (0.0002)
N	3,915,249	744,096	936,427	129,513
R^2	0.50	0.49	0.49	0.47

Table 3.1: Regression results for estimating equation (3.3). Standard errors are in parenthesis. Additional control variables include dummies for gender, occupation, industry, year, as well as worker age, worker age squared and firm age. All years are pooled. See Table 3.10 in Appendix A.14 for an extended version. Data source: SIEED

higher for West Germany in the SIEED.[24] Additionally, the median firm-level share as well as the 75% quantile are higher in West Germany, and West Germany features a larger dispersion across firms.

One potential explanation for these observed differences in the high-skill share distribution are differences in the industry and size composition across the regions in combination with a strong correlation between industry or size on the one hand and the skill share on the other hand. To explore these relationships, Figure 3.23 in Appendix A.9 shows the share distribution by industry, while Figure 3.7 additionally provides a slice across four different firm size groups. Indeed, the average as well as median high-skill shares are increasing in firm size, except for the largest size bin which suffer from a low number of observations. However, the dispersion of shares within each size groups stays high and the larger mean and median share across firms in West Germany also hold for the three bottom size groups. This implies that size differences are not the single driver for differences in the firm-level high-skilled share. Regarding the relationship between high-skilled share and industry, Figure 3.23 reveals large differences across industries, but no clear picture emerges when comparing East and West Germany. The results of a regression of firm size, age, and industry as well as the region on the high-skill share are presented in Table 3.9 in Appendix A.10. The table shows that a 1 percent larger firm is estimated to have a 1.2 percentage point larger high-skilled share confirming the positive relationship when controlling for firm characteristics.[25]

Before estimating the effect of the workforce composition within the firm on wages controlling for size and industry, Figure 3.26 in Appendix A.13 plots the firm-level

[24] The difference presented in the figure is smaller than the one obtained from the SIAB, as I pooled all years.

[25] Including an interaction term between firm size and East Germany is not significant implying the same size-share gradient across the regions.

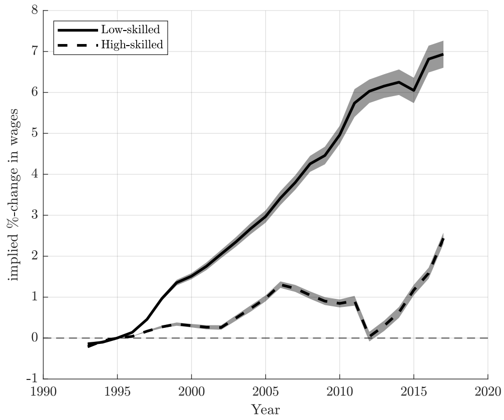


Figure 3.8: Counterfactually implied change in wages by worker type, based on yearly regressions of type (3.3) and the difference between the share of high-skilled worker in West Germany and East Germany. The shaded areas represent 95% confidence intervals. Data source: SIEED/SIAB

average wages for low- and high-skilled workers by firm share and firm size bins for East and West Germany. Apart from the well known positive size-wage relationship, a positive share-wage gradient is visible within each size bin for both worker types.

To estimate the marginal effect of a larger high-skilled share at the firm level on individual wages, I use the following equation

$$\log(w_{it}) = \alpha + \beta Share_{it} + \delta Size_{it} + \gamma X_{it} + u_{it} \tag{3.3}$$

where β is the main coefficient of interest, $Share_{it}$ measures the ratio of high-skilled workers to all workers within the firm of worker i in year t, and $Size_{it}$ represents log employment of the firm. X contains additional control variables in the form of dummies for gender, occupation, industry, year, as well as worker age, worker age squared and firm age. To detect any differences between East and West Germany as done by Bachmann et al. (2022) for firm size only, I run separate regressions for each region and skill type. Table 3.1 lists the results.[26] Not surprisingly given Figure 3.26, a positive relationship between the high-skill share and wages is obtained. However, the magnitude of this semi-elasticity differs greatly between East and West Germany and for low and high-skilled worker: it is stronger for East Germany and stronger for low-skilled, respectively.[27] Regarding the size-wage elasticity, I obtain values in the ballpark of the ones reported in Bachmann et al. (2022). Interestingly, I find stronger differences in the elasticities across the regions for high-skilled workers and a very small gap for low-skilled workers.

[26] Appendix A.14 shows the results without censored wages and with imputed wages. The results are very similar.

[27] This finding is in line with Jarosch et al. (2021) which finds a positive relationship between the composition of the workforce and wages especially for less paid workers in the firm.

To give some meaning to these results, a low- (high-)skilled worker in East Germany is estimated to earn about 8.6% (4.1%) more, when working for a firm with a one standard deviation higher share. These number change to 5.9% and 2.4% for West Germany, respectively. Additionally, I perform the following counterfactual experiment: I compute the change in average wages for workers in East Germany, if East Germany had the West German high-skilled share as depicted in Figure 3.2. To do so, I re-run the regressions for each year separately to detect any change in the wage-share elasticity over time. Figure 3.8 plots the implied change in low- and high-skilled wages between 1993 and 2017, as implied by the coefficients of these regressions and the high-skilled worker share gap. The figure shows that in a counterfactual world, where East Germany has the same high-skill share as West Germany, low-skilled wages would be up to 7% higher, depending on the year. This number is twice as large as the one for high-skilled workers and strongly increasing over time, mirroring the trend in the share of high-skilled worker. Note that this measures only the direct effect of working with more high-skilled workers. Given the previous positive relationship between firm size and skill share, it seems likely that a higher economy wide share of high-skilled workers further affects wages by generating additional endogenous responses in the firm distribution. Moreover, this figure does not take the mechanical effect from the previous section into account. To quantify the direct as well as indirect effects of the skill shortage in East Germany properly, a structural model is needed embedding the effects on the firm workforce composition.

4 Model

This section lays out the quantitative model used to analyze the effect of a lower relative supply of high-skilled workers on wages and productivity taking the effects on the firm distribution into account. The model builds on Kaas and Kircher (2015) which provide a tractable framework with *large* firms operating in a frictional labor market. In a nutshell, firms in the model face convex vacancy posting costs, leading to a trade-off between offering higher wages to attract more applicants or to post more vacancies, thereby featuring wage heterogeneity across the firm distribution. Now, in the presence of ex-ante heterogeneous workers, firms need to decide on their optimal workforce composition and on the implementation considering this trade-off. The decision of firms does not only depend on their current productivity and workforce, but also on their ex-ante heterogeneous type. In equilibrium, this implies that the cross-sectional firm distribution features heterogeneity among firm size, workforce composition as well as the wage structure. I do not consider idiosyncratic or aggregate shocks to keep the model simple as most heterogeneity across firms is driven by permanent firm differences and I am interested in a comparison between two steady states. Finally, time is discrete and runs forever.

4.1 Economy

The economy is populated by two types of agents: workers and firms. All types of agents discount the future with a common discount factor β, live infinitely, and are risk neutral. The mass of workers is normalized to unity. Workers can be either employed or unemployed and differ in terms of their permanent productivity $x_L < x_H$. Mirroring the empirical section, I refer to x_L workers as low-skilled and to x_H workers as high-skilled. Their population shares are given by μ_L and μ_H, respectively. During unemployment, workers receive unemployment benefits $b(x) \geq 0$ depending on their permanent productivity level. To account for the observed heterogeneity in firm size and workforce composition from Section 3.4, firms differ in their permanent productivity y and in their permanent type $z \in \{z_L, z_H\}$. As will be discussed in Section 5, firms of type z_H will be relatively more high-skill intensive than firms of type z_L. The mass of firms in the economy is endogenous. Firms are either potential entrants into the labor market or incumbents. Potential entrants of each type z decide whether they want enter or not. When firm enter, they have to pay setup costs $K(z)$ depending on their type, afterwards they draw their productivity level y with probability $g_y(y)$, and become incumbent. Incumbent firm employ a continuum of workers of each type (n_L, n_H), occur a fixed cost of operation f per period, and produce according to the production function $F(y, z, n_L, n_H)$. Moreover, each period with exogenous probability $\delta_0(y)$ firms have to exit the market and a fraction s_0 of each worker type quit their employment relationship. All firms in the market optimize over their exit probability $\delta > \delta_0(y)$, the share of each worker type to lay off (s_L, s_H) with $s_L, s_H > s_0$, and the number of vacancies (V_L, V_H) to post for each type.[28] Posting vacancies generates posting costs of $C(V_L, V_H, n_L, n_H, z)$. The parameterization of the vacancy post function as well as the production function mainly affects the within composition of a firm and the paid wages, respectively. While the exact choice for these functions is guided by the empirical findings related to the size-share as well as the share-wage relationships (discussed in detail in Section 5), it is kept generic in the remainder of this section. If a firm posts vacancies, it must also specify a corresponding contract $\mathfrak{C}$ which promises (life-time) utility W to a worker. By assumption, all applicants of identical type are offered the same contract. Unemployed workers direct their search towards firms with the most attractive offers. There are no job-to-job transitions. Due to frictions on the labor markets, a matching function determines the number of newly generated matches given the number of vacancies and the number of appli-

[28] Since school leaving qualification is observable and often specified in vacancy postings, I assume that firms post specific vacancies for low and high-skilled separately.

cants. Hence, firms take as given that promising W attracts λ applicants leading to a job-filling probability of m.

4.2 Timing

Each period is subdivided into five stages. In the first stage, potential entrants decide on entering the market and draw their permanent productivity in case they do. In the second stage, knowing their productivity y and type z, firms decide on exiting the labor market. If they stay, they choose the share of workers to fire and the number of vacancies to post. At the same time they also re-design existing contracts. In the fourth stage, applicants arrive at each sub-market and are matched to vacancies. Separated workers start to search for jobs in the next period. In the final stage, output is produced and wages as well as unemployment benefits are paid.

4.3 Contracts

Contracts are complete and all parties fully commit to them. I assume that contracts are recursively defined, i.e., firms can change the details each period as long as the promised value is maintained. These details consists of the current wage w, the next-period separation probability s, the future firm exit probability δ, and the remaining promised value for next period W'. I assume that firms deliver W by a constant flow of wages w. Thus, a contract for worker type x can be summarized by

$$\mathfrak{C}(x) = \left\{w, s(y,z,x), \delta(y,z), W'(y,z,x)\right\}.$$

4.4 Problem for the Worker

Due to the focus on firms, the worker side is kept simple: After observing all offered contracts and their promised values, unemployed workers search for the most valuable contract, and enter the corresponding sub-market. They take into account that a higher promised value W attracts more applicants, reducing their own job-finding probability $m/\lambda(m)$. The value of unemployment for a worker of type x is given by

$$U(x) = b(x) + \beta \max_{W} \left[\frac{m(W,x)}{\lambda(m(W,x))} W + \left(1 - \frac{m(W,x)}{\lambda(m(W,x))}\right) U(x) \right]$$

and consists of two components. The first component describes the flow value of unemployment benefits $b(x)$. The second component represents the highest discounted expected value for the period across all sub-markets characterized by W: with probability $m(W,x)/\lambda(m(W,x))$ a worker finds a job in this sub-market and receives a promised life-time utility W. With the complementary probability, a worker stays unemployed.Due to the time-invariant nature of this expression, it is useful to consider the equivalent expression

$$(1-\beta)U(x) = b(x) + \underbrace{\beta \max_{W} \frac{m(W,x)}{\lambda(m(W,x))}\left[W - U(x)\right]}_{\rho(x):=}. \tag{3.4}$$

This expression equates the flow value of unemployment to the unemployment benefits and the option value from searching $\rho(x)$. Note that $\rho(x)$ is the same across all sub-market for workers of the same type as a worker would not direct her search to less attractive offers and firms would not offer a higher value than necessary. Therefore, given $\rho(x)$, this equation pins down the equilibrium relationship between W and m (or λ): If a firm wants to fill a vacancy for worker type x with probability $m > 0$, it needs to promise a value of

$$W(x) = U(x) + \frac{\lambda(m)}{m}\frac{1}{\beta}\rho(x)$$

Employed workers face no decision as there are no job-to-job transitions and firms at each point in time promise a value that makes employment for workers more attractive than unemployment. Letting $\varphi := (1-s)(1-\delta)$ denote the retention probability of the worker, the value for workers employed with contract $\mathfrak{C}(x)$ at a firm with productivity y and type z is

$$W(x) \equiv W(y,z,x,\mathfrak{C}(x)) = w + \beta\mathbb{E}\left[(1-\varphi(y,z,x))U(x) + \varphi(y,z,x)W'(y,z,x)\right]. \tag{3.5}$$

4.5 Joint Surplus Optimization

As discussed in Appendix B.1, the complicated firm problem with the re-optimization of contracts is equivalent to first optimizing the sum of the values of all workers at the firm and the firm's value and then, second, solving for the contracts that implement the allocation, e.g., the wage schedules and separation probabilities.

The joint value of a firm and its workers at the production stage is given by

$$\begin{aligned} JS(y,z,n_L,n_H) = \max_{\delta,\{V_i,W_i,s_i\}} \; & F(y,z,n_l,n_H) - f \\ & + \beta\mathbb{E}\Bigg[\delta \sum_{i\in\{L,H\}} U(x_i)n_i + (1-\delta)\times\Bigg\{\sum_{i\in\{L,H\}} U(x_i)n_i s_i \\ & - C(V_L,V_H,n_L,n_H,y,z) - \sum_{i\in\{L,H\}} m(W_i,x_i)V_iW_i \\ & + JS(y,z,n'_L,n'_H)\Bigg\}\Bigg] \end{aligned} \tag{3.6}$$

s.t.

$$n_i' = (1 - s_i)n_i + m(W_i, x_i)V_i \quad i \in \{L, H\} \tag{3.7}$$

and taking the relationship between W and m from equation (3.4) into account. To simplify notation, I assume that all workers get the same contract in terms of the separation rate s as it is not pinned down in equilibrium. The first part of (3.6) denotes the flow production and the operation costs. If the firm chooses to leave the market, the value of the firm is zero but each worker's continuation value is given by the value of unemployment $U(x_i)$, implying a total continuation value of $\sum_i U(x_i)n_i$. Similarly, if the firm does not exit but chooses to lay off a share s of its workforce, all separated worker together contribute $\sum_i U(x_i)n_i s_i$ to the joint value. Additionally, the firm-worker group needs to pay vacancy posting costs $C(\cdot)$ and the promised value for new hires which are also costs from the view of the already matched workers. Finally, equation (3.7) states that future employment is the sum of the remaining workforce and new hires.

4.6 Firm Entry

Next, consider one of the infinitely many potential entrants. Such a firm can enter the market after paying the entry costs of $K(z)$ corresponding to its type. Then, it draws a productivity y from the distribution $g_y(y)$. After seeing its productivity, it behaves as an incumbent by choosing the number of workers to hire but due to the absence of an existing workforce, it does not have to choose a separation rate. Note that a firm can exit the market in the period of entering after its productivity is revealed. The value of an entrant of type z in the stage after drawing the productivity y is given by

$$JS^e(y,z) = \max_{V_L^e, V_H^e, W_L^e, W_H^e} \left[JS(y, z, n_L^e, n_H^e) - C(V_L^e, V_H^e, 0, 0, y, z) - \sum_{i \in \{L,H\}} n_i^e W_i^e \right]^+ \tag{3.8}$$

where $(\cdot)^+$ is defined as $\max(\cdot, 0)$ incorporating the exit decision δ^e and

$$n_i^e = m(W_i^e, x_i)V_i^e \qquad i \in \{L, H\}. \tag{3.9}$$

This equation facilitates the fact that a new entrant becomes an incumbent and operates under the same value function after hiring and paying for its initial set of workers. Since there are infinitely many potential entrants of each type, firms enter until the expected value of entering equals the entry costs

$$K(z) = \sum_y g_y(y) JS^e(y,z) \tag{3.10}$$

4.7 Firm and Worker Dynamics

To shorten notation, write the state and control variables as vectors by defining $\boldsymbol{n} = (n_L, n_H)$, $\boldsymbol{V} = (V_L, V_H)$, $\boldsymbol{W} = (W_L, W_H)$, and $\boldsymbol{s} = (s_L, s_H)$. Let $f(y, z, \boldsymbol{n})$ denote the mass of firms with productivity y, type z, and $\boldsymbol{n}$ worker at the very beginning of a period. Furthermore, let $N^e(z)$ define the mass of new entrants. Then, the distribution of firms being in state $(y, z, \boldsymbol{n}')$ next period is given by

$$\begin{aligned} f'(y, z, \boldsymbol{n}') = \sum \mathbb{1}_{\{m(\mathbf{W}(y,z,\boldsymbol{n}))\boldsymbol{V}(y,z,\boldsymbol{n})+(1-\mathbf{s}(y,z,\boldsymbol{n}))\boldsymbol{n}=\boldsymbol{n}'\}}(1-\delta(y,z,\boldsymbol{n}))f(y,z,\boldsymbol{n}) \\ + N^e(z)\mathbb{1}_{\{m(\mathbf{W}^e(y,z))\boldsymbol{V}^e(y,z)=\boldsymbol{n}'\}}(1-\delta^e(y,z))g_y(y). \end{aligned} \tag{3.11}$$

The first part relates to all currently active firms with productivity y, which chose not to exit and are left with $\boldsymbol{n}'$ workers. Similarly, the second part accounts for the mass of firms entering the labor market, drawing y, and then hiring $\boldsymbol{n}'$ workers.

The unemployment rate for worker type x_i evolves according to

$$\begin{aligned} u_i' = \sum_{y,z,\boldsymbol{n}} n_i \left[\delta(y,z,\boldsymbol{n}) + (1-\delta(y,z,\boldsymbol{n}))s_i(y,z,\boldsymbol{n})\right] f(y,z,\boldsymbol{n}) \\ + \sum_{y,z,\boldsymbol{n}} (1-\delta(y,z,\boldsymbol{n}))f(y,z,\boldsymbol{n}) \left(1 - \frac{m(W_i(y,z,\boldsymbol{n}), x_i)}{\lambda(m(W_i(y,z,\boldsymbol{n}), x_i))}\right) V_i(y,z,\boldsymbol{n}) \\ + \sum_{y,z} N^e(z)(1-\delta^e(y,z))g_y(y) \left(1 - \frac{m(W_i^e(y,z), x_i)}{\lambda(m(W_i^e(y,z), x_i))}\right) V_i^e(y,z) \end{aligned} \tag{3.12}$$

where the first line tracks all workers who separate from firms, and the second (third) line accounts for all workers who search for jobs at incumbent (entrant) firms but are not successful. Since only previously unemployed workers can search, the number of unemployed workers of each type u_i has to be equal to the applicants at all firms at the end of the period:

$$\begin{aligned} u_i = \sum_{y,z,\boldsymbol{n}} (1-\delta(y,z,\boldsymbol{n}))f(y,z,\boldsymbol{n})\lambda(m(W_i(y,z,\boldsymbol{n}), x_i))V_i(y,z,\boldsymbol{n}) \\ + \sum_{y,z} N^e(z)(1-\delta^e(y,z))g_y(y)\lambda(m(W_i^e(y',z), x_i))V_i^e(y,z) \end{aligned} \tag{3.13}$$

where, again, the first part represents applicants at surviving incumbent firms and the second part represents applicants at new entrants. Additionally, the beginning-of-period mass of employment workers is given by

$$e_i = \int\int\int f(y,z,\boldsymbol{n})n_i dydzd\boldsymbol{n}.$$

Finally, the aggregate recourse constraints (defined again at the beginning of a period)

$$e_i + u_i = \mu_i \quad i \in \{L, H\} \tag{3.14}$$

have to hold. They state that the number of job searchers u_i and employed workers e_i has to equal the total mass μ_i for each type $i \in \{L, H\}$ in the economy.

4.8 Equilibrium

Assuming a unique mapping between $\rho(x)$ and $K(z)$ as well as an exogenous share μ_H of high-skilled workers in the economy that is above the implied share of high-skilled workers and job-seekers at one firm type z_H and below the implied share at the other firm type z_L, the more general conditions of Kaas (2021) are satisfied. These imply that there exists a unique, *block-recursive* equilibrium. The main beauty of these types of equilibria is that equilibrium policy functions can be solved without the knowledge of the cross-sectional (firm) distribution, as the following definition of the equilibrium makes clear.

Definition 1. *A block-recursive equilibrium of this economy consists of a set of value functions $U(x), W(x), JS(y, z, n_L, n_H), JS^e(y, z)$, and a decision rule for unemployed workers where to search, decision rules for entering firms $\{V_L^e(y, z), V_H^e(y, z), W_L^e(y, z), W_H^e(y, z), \delta^e(y, z)\}$ as well as for incumbent firms $\{V_L(y, z, n_L, n_H), V_H(y, z, n_L, n_H), W_L(y, z, n_L, n_H), W_H(y, z, n_L, n_H), \delta(y, z, n_L, n_H)\}$ s.t.*

1. *The value and policy functions are independent of the distribution of agents across states.*
2. *The free entry conditions* (3.10) *are satisfied for each type.*
3. *Firms' strategies are optimal; they solve the joint optimization problem* (3.6) *with corresponding joint value JS.*
4. *Entrants' strategies solve the firms' entry problem* (3.8).
5. *Workers' search strategies are optimal, i.e., (U, W) are the value functions associated with the worker's problem* (3.4) *and* (3.5).
6. *The dynamic equations* (3.11) *and* (3.12) *hold.*
7. *The aggregate resource feasibility* (3.14) *is satisfied.*
8. *The assumptions of this section hold.*

Appendix B.2 lays out the numerical computation of the equilibrium and the next section discusses the calibration of the model.

5 Calibration

I calibrate the model in weekly frequency to the East German labor market in 2015 –the last year with full information in all datasets– to gauge the quantitative contribution of the lower high-skill worker share for the lower wages and smaller firms in East Germany.

In general, the calibration follows Kaas and Kircher (2015) but is adjusted to account for the presence of different worker and firm types. To capture heterogeneity in job-filling and job-finding rates by worker skill, I assume the same functional form for the matching function as in Kaas and Kircher (2015), but with different parameters for worker type i

$$m_i(\lambda) = \left(1 + k_i \lambda^{-r_i}\right)^{-1/r_i}.$$

While the matching function is assumed to be different for the two worker types, each matching function is calibrated in the same way as in Kaas and Kircher (2015). Following Mueller et al. (2022), I assume that unemployment benefits for each worker type i are given by a constant fraction b of their labor productivity, $b_i = b \cdot x_i$. Then, b is calibrated to match the replacement rate (b over economy-wide average wage) of 60%. The total mass of workers in the economy is normalized to unity, and the mass of high-skilled workers μ_H is set to 17.35%, the share of high-skilled unemployed and employed individuals in the SIAB for East Germany in 2015. Worker specific productivity is calibrated as follows: the productivity for low-skilled workers x_L is normalized to one, and the productivity for high-skilled workers x_H is set to target a skill premium of 16.27% from the regression with demographic and occupation specific controls, as these sources of heterogeneity are not modeled.

To account for the additional worker and firm heterogeneity, the vacancy posting cost function and the production function have to be adjusted, too. The vacancy posting costs are assumed to be the sum of the posting costs for each worker type i from Kaas and Kircher (2015) with different cost parameters $c_{i,z}$ depending on the worker and firm type[29]

$$C(V_L, V_H, n_L, n_H, y, z) = \sum_{i \in \{L,H\}} \frac{c_{i,z}}{1+\gamma} \left(\frac{V_i}{n_i}\right)^{\gamma} V_i.$$

This specification simplifies to the one in Mueller et al. (2022) in the absence of firm types and keeps the model tractable since the additive separability implies that the optimal implementation of the hiring decision for one worker type does not depend on the other type.

As wages are determined by the trade-off between posting more vacancies with higher posting costs and a higher promised wage to attract more applicants resulting

[29]Following Kaas and Kircher (2015), I use $\bar{n}_i = n_i + 1$ to avoid divisions by zero.

Par.	Description	Target	Source
		Agents	
β	Discount factor	Annual interest rate of 5%	
b	UI fraction of labor prod.	60% replacement rate	OECD[30]
μ_H	Mass of high-skilled workers	High-skilled population share of 17.35%	SIAB (2015)
		Production	
α	Production function elas.	Labor income share of 2/3	Berger and Wolff (2017)[31]
x_L	Low-skilled productivity	Normalized to 1	
x_H	High-skilled productivity	Skill premium of 16.27%	SIAB (2015)
f	Fixed cost of production	No endogenous exit; set to 0	
q_L	Low-skilled intensity: z_L firms	Mean firm-level high-skilled share	SIEED (2015)
q_H	Low-skilled intensity: z_H firms	Share firms with high-skilled share <20%	SIEED (2015)
		Firms	
(y_L^j)	Productivities of z_L firms	Employment shares (4 size classes)	BHP (2015)
(y_H^j)	Productivities of z_H firms	Empl. shares of >20%-share firms by size	SIEED (2015)
(σ^j)	Firm entry shares	Firm shares (4 size classes)	BHP (2015)
(δ_0^j)	Exit rates	Annual firm exit rates (4 size classes)[32]	BHP (1993-2017)
		Matching	
s_0	Quit rate	Monthly quit rate of 0.24%	SIAB (2015)[33]
$c_{L,z}$	Recruitment cost scale par.	Wage high-skill share elasticity by skill	SIEED (2015)
$c_{H,z}$	Recruitment cost scale par.	Monthly job-finding rate by skill	SIAB (2015)
r_i	Matching function elasticity par.	Monthly job-filling rate by skill	[34]
k_i	Matching function scale par.	Job-filling rate wrt. lambda of 0.72	Shimer (2005)
γ	Recruitment cost elasticity par.	Literature	Mueller et al. (2022)
$K(z)$	Entry costs	Normalization	

Table 3.2: Calibration targets and associated parameters

in a higher vacancy filling rate, the cost parameters $c_{i,z}$ crucially affect this choice. To a lesser extent, they also affect the steady state employment composition by influencing the cost to maintain the workforce.

In contrast to the additive separability of output by worker type in Mueller et al. (2022), I assume that the worker types are complements in the production process. This has two main benefits. First, mechanically, it allows for a relatively simple calibration of firm types by within-firm share, as the output elasticity of each worker type nearly aligns with the steady state share of the firm in equilibrium. Second, micro-founded models about firm organization as well as the recent literature on peer effects suggest strong complementarities across workers which would not be present in a model with additively separable output by worker type where the firm could

[30] Gross replacement rates are 60% for childless workers in Germany according to the OECD (see https://stats.oecd.org/Index.aspx?DataSetCode=NRR).

[31] Berger and Wolff (2017) estimate the income share for Germany to be between 60% and 70%.

[32] Annual firm exists takes into account the additional information contained in the BHP as mentioned in Section 2.3.

[33] For spells with available information, about 20% of all separations are either due to the worker quitting or a joint agreement in the SIAB.

[34] In 2014, the average duration between starting to search and deciding for an applicant was 61 (75) calendar days for jobs with low (high) skill requirements. The implied weekly filling rates are very close to the ones for Austria used in Mueller et al. (2022).

be split in half not affecting output. Additionally, the complementarities allow for potential future policy exercises studying the effect of policies for one worker type on the other worker type. In particular, I impose the following production function

$$F(y, z, n_L, n_H) = y(z)\left((x_L n_L)^{q_z}\,(x_H n_H)^{1-q_z}\right)^{\alpha}$$

with different (nested) output elasticities of low-skilled labor as well as different firm productivity $y(z)$ for the two firm types. This function generalizes the production function of Kaas and Kircher (2015) by replacing the homogeneous labor input with the Cobb-Douglas aggregate of low and high-skilled labor. Whereas q is the main determinant for the steady state within firm distribution, $y(z)$ affects the overall size of the firm.

I assume that the two firm types z draw the four y-states for their type with the same probabilities $\sigma(y)$ targeting the firm shares by size. This choice will prevent the model from explaining the existence of more very large firms in West Germany as shown in Section 7. While calibrating different probabilities is in theory possible by additionally targeting the firm level shares by high-skill share within firms, I decided against it for two reasons. Not only would it make the model more complicated and the effects in the experiment harder to track, the number of firms in East Germany in 2015 is too low to be very reliable. However, I assume that these y-states are different by firm type to account for the increasing employment shares of high-skilled intensive firms by firm size.

I jointly calibrate q, y, and c_i for each firm type in the following way: First, q is set to target the share of firms with less than 20% of high-skilled workers as well as the firm-level average high-skill share. Second, I target the employment shares by firm size as well as the employment shares of firms with more than 20% high-skilled share by firm size. This informs the productivity levels $y(z)$. Third, I set the four parameters of the vacancy posting cost function $c_{i,z}$ to match the vacancy filling rates for low and high-skilled workers as well as the wage-share semi-elasticity.

All other parameters are calibrated analogously to Kaas and Kircher (2015). Note that I choose four instead of five firm size classes, as there are few very large firms in the sample, in particular for East Germany. Since this is especially true for a single year in the SIEED, I use the larger BHP wherever possible and required. Table 3.2 provides an overview of the mapping between the model parameters and the calibration targets. I follow Mueller et al. (2022) and set the vacancy posting cost elasticity γ to 0.5.

The calibrated parameters are reported in Table 3.3. Two sets of parameters are especially noteworthy. First, the calibrated permanent productivity levels for firms

[34]Generally, the BHP and the SIEED imply similar values for the firm size distribution, however the SIEED features higher employment at the largest establishments. See Section 6.2 for a related point.

Externally calibrated

	β	b	α	s_0	γ
	0.999	0.60	0.6666	0.0024%	0.5
by worker type i	μ_i	x_i	r_i	k_i	
L	0.8265	1.0000	0.6649	10.1623	
H	0.1735	1.1627	0.5843	7.8715	

Internally calibrated

by firm type z	$K(z)$	q_z	$c_{L,z}$	$c_{H,z}$
z_L	169.28	0.86	0.5	0.5
z_H	148.08	0.70	50.0	3.5
by firm prod. type j	(σ^j)	(δ_0^j)	(y_L^j)	(y_H^j)
1	99.3777%	0.189%	0.5092	0.7566
2	0.5920%	0.046%	1.4100	2.0000
3	0.0255%	0.025%	2.0500	3.2000
4	0.0048%	0.015%	2.8140	4.9000

Table 3.3: Calibrated parameter values. See Table 3.2 for parameter descriptions.

differ to a large degree by firm type. However, due to decreasing returns to scale, differences in average labor productivity are significantly smaller than anticipated as discussed in Section 6.2. Second, the vacancy posting costs parameters differ by a factor of 10 and 7 for low and high-skilled, respectively, translating to the same relative difference in average hiring costs by firm type. While z_L firms pay recruitment costs roughly equal to a monthly wage[35], average recruitment costs for z_H firms are on average equal to 10 months of wage payments. While these costs are on the larger side, they can capture additional screening or searching costs when using more expensive or multiple search channels, or bonus payments.

Section 6.2 discusses the model fit in detail showing the empirical moments vis-à-vis the model generated moments in Table 3.4.[36]

[35] This is in line with the results from Gürtzgen et al. (2019) which document that the average costs to fill a permanent vacancy costs about 19 labor hours and 1244 Euro using the German Job Vacancy Survey of the IAB in 2018.

[36] To obtain the implied moments regarding wages, I simulate a panel of 100,000 firms for each firm type z for up to 20,000 periods and re-weight them according to their endogenous shares in the economy.

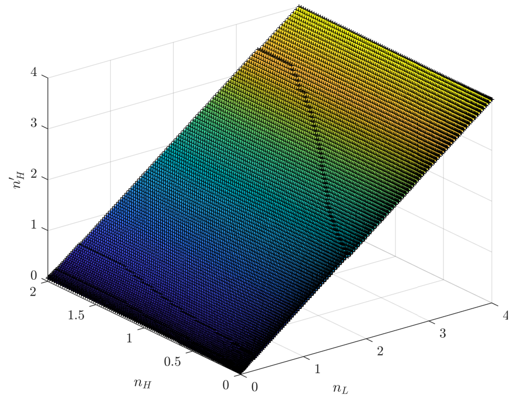
6 Results

6.1 Firm Behavior

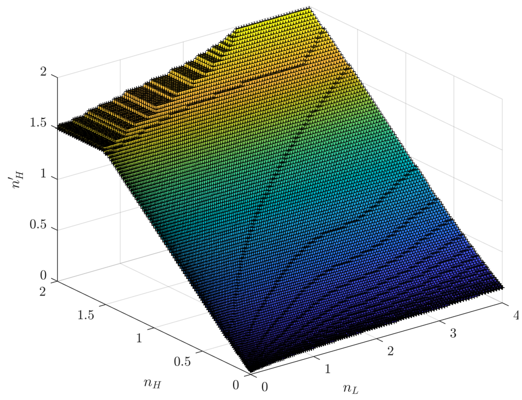
In this section, the behavior of firms in equilibrium is explained. Note that the model does not feature idiosyncratic productivity shocks as discussed in Section 5. For illustration, Figure 3.9 displays the firms decision rules for next period's employment. To gauge how the new employment level is reached, Figure 3.10 shows the posted wages of firms. To keep the amount of figures at a reasonable level, these two figures are from the perspective of the least productive firm of each type z. Finally, Figure 3.11 plots the steady state distribution of firms implied by these decisions.

I start with discussing the employment decision presented in Figure 3.9. Due to the presence of convex hiring costs introduced by the vacancy posting cost function $C(\cdot)$, firms do not immediately jump to their optimal (steady state) size as discussed extensively in Kaas and Kircher (2015) for a single worker and firm type. Instead, firms grow slowly over time, minimizing the total cost they have to pay. In the figure, this can be seen by the gradual increase in the future choice of the number of workers n_i' as the current number of workers of the same type n_i becomes larger. In contrast, if vacancy costs were linear, a firm below its optimal size would jump directly to this level independently of its current workforce, implying a flat policy function. However, the model does imply a region where this policy function is flat: if the firm happens to have so many workers, that the marginal productivity (due to decreasing returns to scale in the production function) is too low to offset the costs associated with retaining the same workforce, the firm actively separates from some of its workers $s > s_0$. While the fraction of separated workers varies with the current size of the firm, the new size will be the same. In equilibrium, these endogenous separations can only happen with idiosyncratic shocks if the firm grew sufficiently large with a high productivity shock and then received a bad shock. In that case, as discussed in Kaas and Kircher (2015), firms do not separate with their workers until their new (long-run) optimal size is reached, but rather choose a slightly higher value to "buffer" the exogenous separation of workers in the subsequent period.

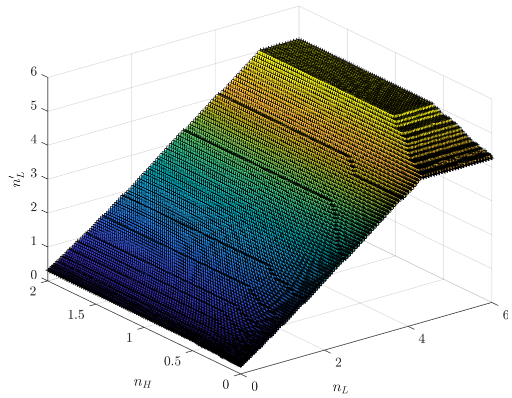
While Kaas and Kircher (2015) considers a single worker type and Mueller et al. (2022) assumes that worker types are completely independent within the firm, hence not affecting the decision of firms, worker types are complements in production in this model. This implies that the policy functions of firms regarding the size of the workforce of one type is not constant in the current size of the workforce of the other type. Instead, the firm wants to, e.g., hire more high-skilled workers if it already has a lot of low-skilled workers, as their marginal product is higher. However, in the absence of idiosyncratic shocks, firms are mostly in the region where the decision for future employment of worker type i does not depend much on the current number of



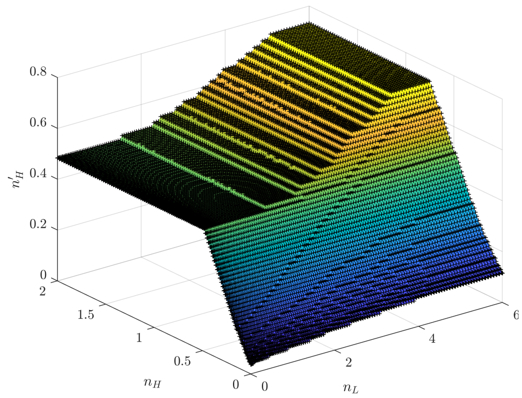
(a) n'_L decision for firm type z_H



(b) n'_H decision for firm type z_H



(c) n'_L decision for firm type z_L

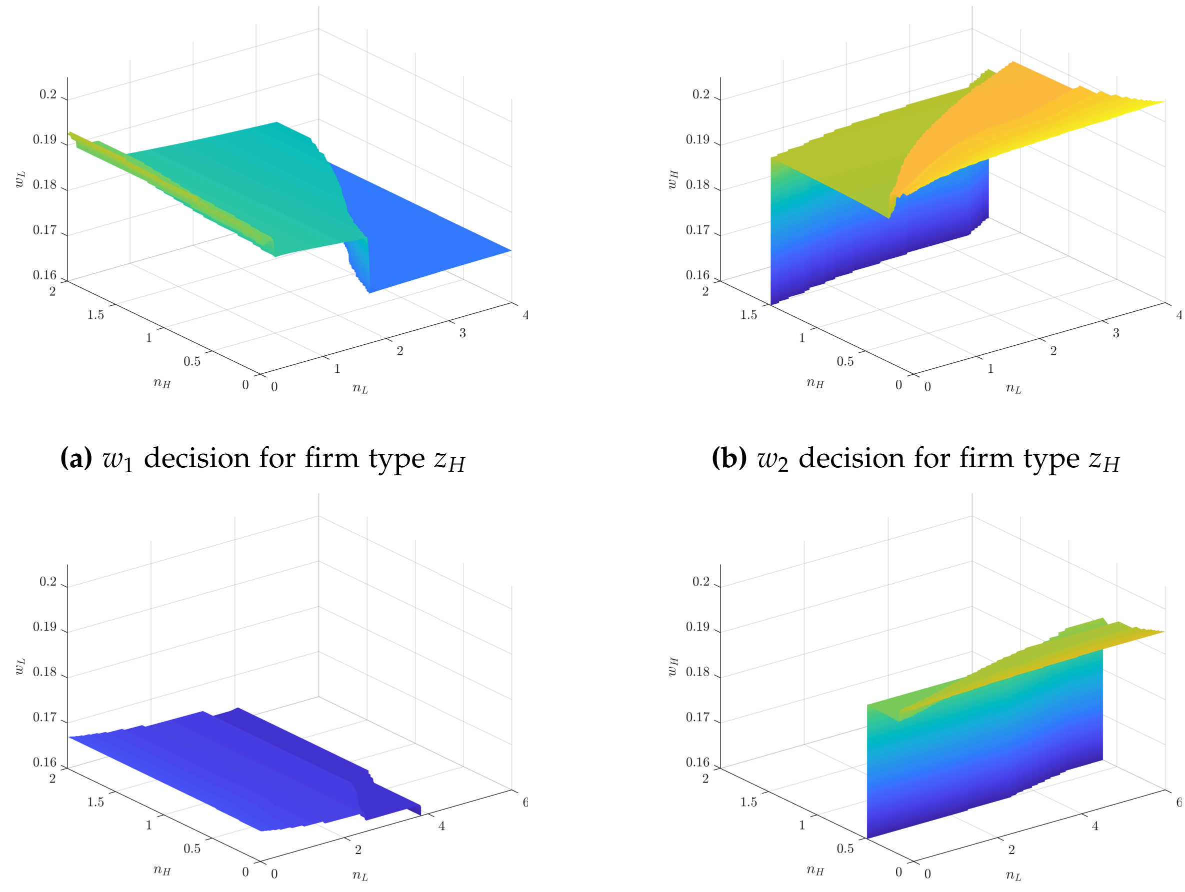


(d) n'_H decision for firm type z_L

Figure 3.9: The four panels show the employment policy regarding the two worker types as a function of the current workforce for each firm type given the lowest productivity draw.

workers of type j. This is driven by the high vacancy costs for low levels of employment of type i dominating over the higher marginal value of workers if employment of the other type is high. Therefore, the decisions of firms are more strongly affected by the complementarities between workers for high values of current employment where firms decide to fire workers and (future) vacancy costs are less important. In general, the complementarities would more directly translate to differences in the hiring procedure of firms if the vacancy posting cost function took the total number of workers or vacancies in the firm into account and was not the sum of the vacancy costs of the two worker types. But since alternative parameterizations would make the model harder to understand without much to gain, in particular for the case when total vacancies matter as the optimal implementation of hirings can no longer be solved in one dimension for each worker type, I use the simpler specification from Mueller et al. (2022).

Comparing the two different firm types, Figure 3.9 shows that the policy functions mainly differ in terms of the overall magnitude and the relative start of the previously



(a) w_1 decision for firm type z_H

(b) w_2 decision for firm type z_H

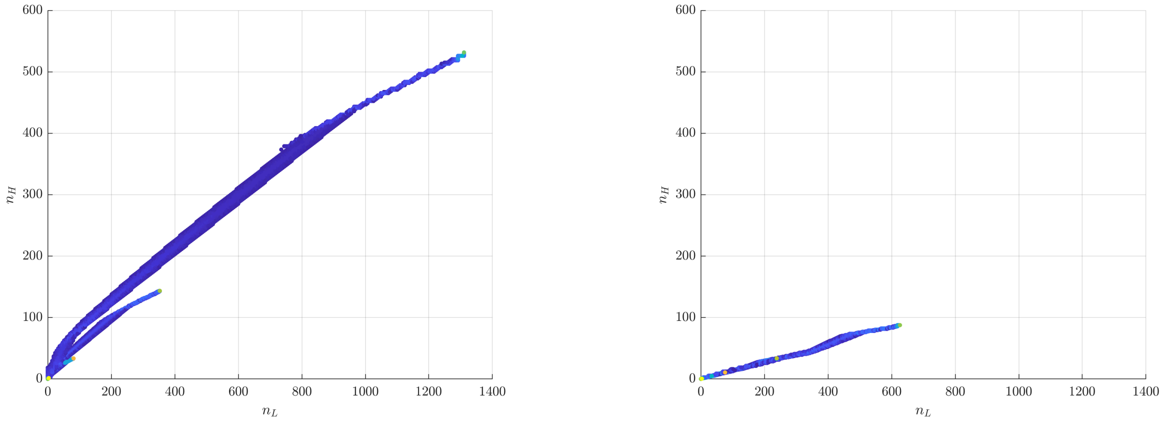
(c) w_1 decision for firm type z_L

(d) w_2 decision for firm type z_L

Figure 3.10: The four panels show the wage policy regarding the two worker types as a function of the current workforce for each firm type with the lowest productivity draw.

described plateau but not in the overall shape. This is mainly driven by the fact that the firm type defines the productivity of the firm and the factor intensity in the production function, thereby determining the overall size as well as the optimal ratio between the two worker types, respectively. Since the low-skilled intensity q is larger for z_L firms than for z_H firms, the latter choose to have a larger share of high-skilled workers. Another force affecting the slope of the decision rules comes from the vacancy posting cost function. As type-z_H firms face larger posting costs, in particular for low-skilled workers, they want to hire those workers slower and to a lower overall extent as their type-z_L counterparts leading to slightly flatter policy functions. Analogously to Kaas and Kircher (2015) and therefore not shown in the figure, firms with a higher productivity level (conditional on type) want to scale up their employment more than low-productivity firms, but face otherwise the same decisions and trade-offs.

To achieve a larger workforce, firms need to hire workers. The firm has two margins to increase the number of new employees: it can either offer a higher value (i.e.,



(a) Firm type z_H **(b)** Firm type z_L

Figure 3.11: The two panels show the firm distribution by employment of each worker type separated by firm type. A brighter color indicates a higher (log) mass of firms.

wage), hence increasing the number of applicants and the job-filling probability per vacancy, or it can post more vacancies. Since both margins present convex costs, the firm chooses the promised wage and the number of applicants for each worker type to minimize the total costs of hiring given the targeted amount of new workers. To analyze how this trade-off is solved for different workers and firms, Figure 3.10 depicts the wage policy for the two firm and worker types by current firm employment. As a direct consequence of the properties of the vacancy posting cost function, and proven in Kaas and Kircher (2015), more productive firms (conditional on size) as well as younger, smaller firms (conditional on productivity) pay higher wages. This is because those firms want to hire more workers as they benefit more from one additional worker, but face higher vacancy posting costs. To avoid these higher posting costs, they increase their job-filling probability by offering a higher wage. A similar story also applies to the two different firm types: as type-z_H firms face higher posting costs, they offer a higher wage and post less vacancies. The higher wages for high-skilled workers mainly arise due to higher unemployment benefits $b(x)$; while both worker types receive the same fraction of their productivity as benefits, high-skilled workers are more productive. In contrast, differences in the hiring procedure of firms play a smaller role.[37]

The policy functions from Figure 3.9 (in combination with the ones for the other productivity levels), lead to the cross-sectional firm distribution depicted in Figure 3.11. The figure shows the mass of firms given the number of L-workers (x-axis) and H-workers (y-axis). For better visibility, I separated the distributions for the two firm types and show larger (log) masses of firms in brighter colors. A careful inspection of the figure reveals that for each firm type, there are exactly four bright

[37]See Section B.2 for the wage formula.

(end-)nodes. These nodes correspond to the four permanent productivity levels and show firms which have reached their optimal steady state size. Given the firm type, all these four nodes imply nearly the same high-skilled share within the firm as the firm composition is mainly driven by the intensity parameter q and not by the vacancy cost function implying little variation in steady state. However, not all firms exhibit the same composition of workers. Now driven by differences in the vacancy posting cost function, firms do not face the same inter-temporal trade-off between the hiring decision of each worker type, and thus hire each worker type with a different pace. The unequal hiring procedure generates heterogeneity in the firm-level high-skilled share conditional on the firm type before the firm has converged to the optimal level of employment given the productivity state. This force is more pronounced for z_H firms, as their vacancy posting costs differ greatly across worker types. In contrast, z_L firms face the same vacancy costs per worker type, hence scaling up their employment evenly when growing. Additionally, in the absence of idiosyncratic shocks, firms quickly converge to their steady state employment level generating little heterogeneity with this channel. As alluded to before, differences in the intensity of low-skilled workers in the production function as well as differences in the vacancy posting costs, lead to hiring procedures and optimal employment (composition) levels that vary across firm types. This circumstance is reflected by the different overall shape of the firm distribution as well as the different location of the bright nodes in the figure.

Finally, due to the block-recursive nature of the equilibrium, these policy functions and distributions, *conditional on firm type*, are independent of the actual distribution of workers in the economy. The mass of each firm type is pinned down by the aggregate resource constraints for both worker types as each firm type implies a different share of high-skilled workers in the population who are currently employed or looking for a job at this firm type. In other words, the more high-skilled workers are in the economy, the more firms will be present that use high-skilled workers intensively for production. The implied mass of each firm type then scales the corresponding distribution and thereby affects all aggregate outcomes. Without the block-recursive structure, policy functions would respond to a change in the (relative) size of the labor force. Since West Germany has a significantly larger high-skilled share than East Germany, the relative supply effect would be very strong in the model and would counter-factually imply that high-skilled wages have to be significantly lower in West Germany. This issue is discussed in Karahan et al. (2019) for a rise in the supply of homogeneous labor, but the argument can be directly applied to the case of heterogeneous workers.

6.2 Model Fit

This section discusses the fit of the model calibrated to the East German labor market in 2015. Table 3.4 provides an overview over all data targets and the corresponding model implied moments. The sources of the data moments as well as the calibrated parameter values are listed in Section 5.

Before discussing how well the model is able to match the firm distribution, I start with the worker side. The replacement rate target and the skill premium are well matched, albeit they are ever so slightly too low. Additionally, the model is able to match the vacancy filling rates for both worker types perfectly but implies a job-finding rate which is up to 2 percentage points below the target. Due to the rich firm heterogeneity, the exogenous calibration of the matching function parameters seems to generate a tension in the model between matching both rates. Since the focus lies on the perspective of firms, I decided to match the vacancy filling rates instead of the job-finding rates which would imply a very high vacancy filling rate.

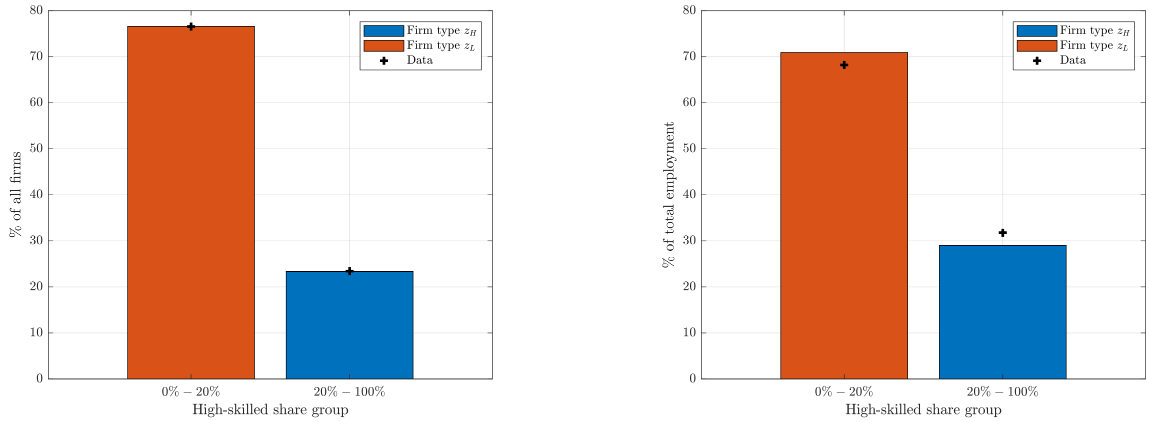
Moving to the firm side, the calibrated model implies that the population share of high-skilled workers would be 28.3% (12.4%) in the presence of a unit mass of firms of type z_H (z_L). As East Germany featured a high-skilled share of 17.35% in the population in 2015, about 23.4% of the firms are therefore calibrated to be of type z_H due

Workers & Matching		
Target	Data	Model
$b/\bar{w}$	0.600	0.591
w_H/w_L	1.163	1.159
Monthly UE_L	0.078	0.058
Monthly UE_H	0.070	0.063
Monthly vac fill. L	0.499	0.499
Monthly vac fill. H	0.406	0.406

Production		
Target	Data	Model
Low-wage elas.	0.451	0.444
High-wage elas.	0.106	0.116
Avg firm share	0.152	0.169
Share >20%-firms	0.234	0.234

Firms (by size)		
Firm shares	Data	Model
$0-49$	0.974	0.974
$50-249$	0.023	0.024
$250-499$	0.002	0.002
$500+$	0.001	0.001
Empl. shares	Data	Model
$0-49$	0.521	0.522
$50-249$	0.311	0.308
$250-499$	0.086	0.087
$500+$	0.082	0.083
Empl. shares of >20%-firms	Data	Model
$0-49$	0.272	0.261
$50-249$	0.282	0.283
$250-499$	0.435	0.356
$500+$	0.444	0.440
Ann. exit rates	Data	Model
$0-49$	0.094	0.094
$50-249$	0.024	0.024
$250-499$	0.013	0.013
$500+$	0.008	0.008

Table 3.4: Empirical Moments and Model Fit



(a) Firm shares

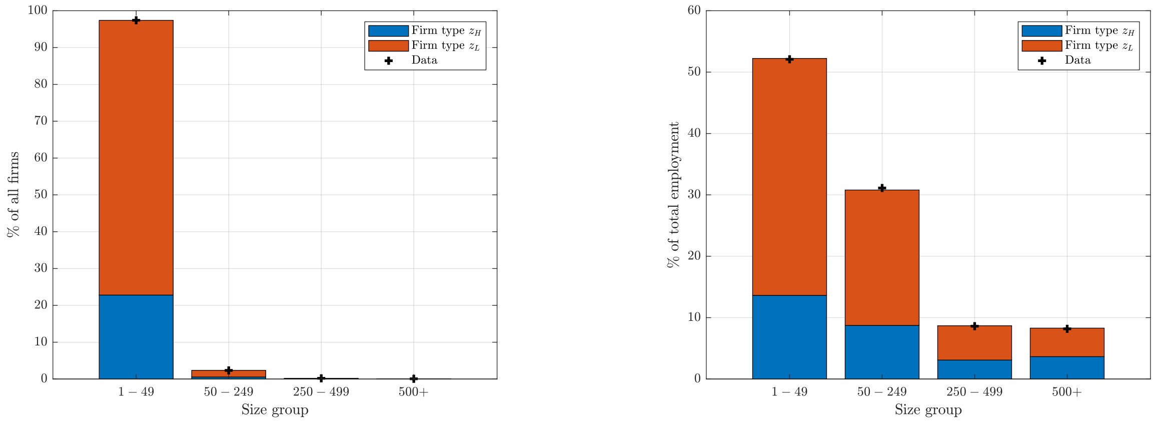
(b) Employment shares

Figure 3.12: The figure shows firm and employment shares by high-skill share and firm type.

to the block-recursivity of the model. In combination with the elasticity parameters q_z implying a firm-level high-skilled share of below 20% for z_L (low-skilled intensive) firms and above 20% for z_H (high-skilled intensive) firms, this endogenously results in a perfect match of the share of firms with more than 20% of high-skilled workers (Figure 3.12a). The fit regarding two other related statistics is also good: the model implies an average firm-level high-skilled share which is only 1.7 percentage points too high. Similarly, the employment share of high-skilled intensive firms is close to the target featuring only a gap of about 2 percentage points as depicted in Figure 3.12b. Since the model is not flexible enough to guarantee an exact match of all these targets, I view this result as a success of the model as it is able to capture the most important characteristics of the firm share distribution despite featuring only two firm types.

Regarding the firm size distribution, Figure 3.13 visualizes the firm and employment shares of Table 3.4 while also distinguishing between the firm types. As in Kaas and Kircher (2015), the model is able to match the two moments very well despite the additional heterogeneity. This is caused by the direct relationship between firm size and permanent firm productivity (conditional on firm type). In the absence of endogenous firm exit, this is also the reason for the good match of the annual exit rates by firm size shown in the table.

Focusing on the two firm types, Figure 3.13 shows that both types are present in all size groups but accounting for different shares of employment. To better understand the relationship between firm size and firm share, Figure 3.14 plots the corresponding fraction of workers employed at firms with a high-skill share of less than 20% conditional on firm size. As the figure shows, the targeted, strong increase in the average high-skilled share by firm size in the data can be replicated by the model. While the data from the SIEED for 2015 implies a sharp increase in the employment



(a) Firm shares **(b)** Employment shares

Figure 3.13: The figure shows the firm and employment shares by firm size and type.

share for firms with more than 250 employees, the model implies a gradual increase over firm size. However, this might be driven by an artifact in the data featuring a low number of firms with 250-499 employees in East Germany in 2015. Pooling all years, the employment share is monotonically increasing with firms of size 250-499 having an employment share exactly in the middle of the two adjacent size groups supporting the model. Since both firm types draw their permanent productivity value corresponding to one of the size groups with the same probabilities σ^i, this implies that z_H firms are, on average, larger.

Next, I consider wages. To visualize the relationship between wages and firm characteristics, Figure 3.15 plots the average wage for each worker type by high-skilled share as well as firm size in relation to the lowest wage among all bins. As the figure shows, the model generates the observed skill premium as mentioned in the beginning of this section. While the model features a positive relationship between firm share and wage, wages are decreasing in firm size. This is especially true for the smallest firms, while wages flatten out among lager firms. Repeating regression 3.3 in the model with firm age, firm size, and the share as independent variables confirms this relationship. Table 3.4 shows that the model matches the wage high-skilled share semi-elasticity. However, the model implies a small, but counter-factually negative elasticity between firm size and wages (around -0.008 for both worker types).

This is caused by the properties of the vacancy posting cost function which is independent of productivity and implies that only the vacancy rate V/L is relevant. Both channels mean that high productive, large firms, which only need to hire a small fraction of their current workforce, pay little for vacancies. Thereby, they are incentivized to use the vacancy margin more extensively resulting in lower wages.

By specifying a different vacancy post function, for example one that takes only total vacancies V and not their rate V/L into account, a positive wage-size elasticity can

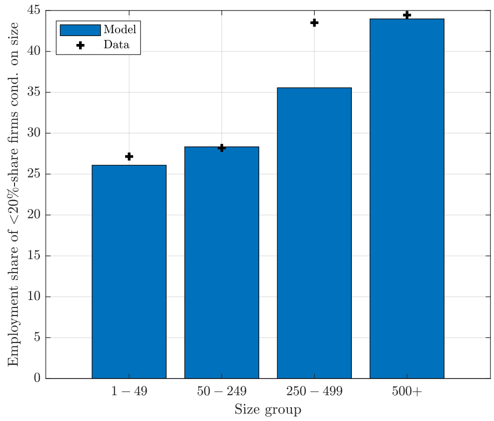
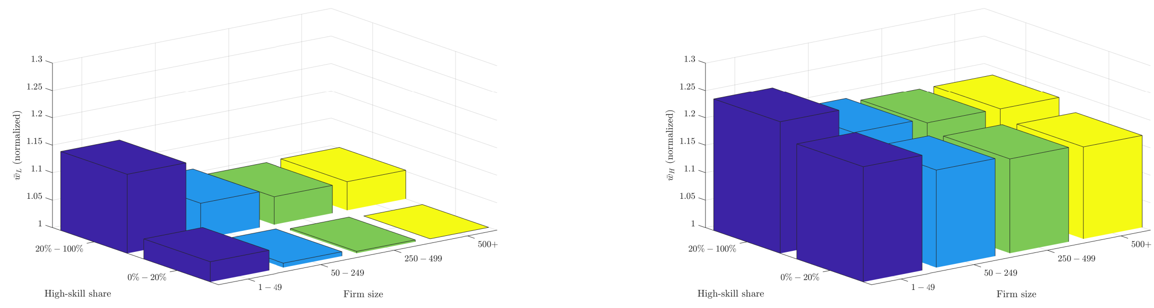


Figure 3.14: The figure shows the employment share of firms with a high-skilled share of 20% or less conditional on size.

be obtained in the model. The reason is that large firms after reaching their optimal steady state size, hire more workers in absolute terms each period than small firms as the same fraction s_0 of workers separates each period. In combination with convex vacancy costs in the level of posted vacancies, this results in large firms offering higher wages to partially offset the higher vacancy posting costs. However, this approach yields two counterfactual predictions. First, as mentioned in Kaas and Kircher (2015) regarding the US, larger firms exhibit lower job-filling rates than small firms. In contrast, avoiding the higher vacancy posting costs would imply higher job-filling rates for large firms. Second, and more mechanical, just increasing vacancy posting costs by firm size would significantly weaken the desire of firms to grow, in particular for high-skill intensive firms facing higher posting costs. To offset this effect, these firms would need to feature an unrealistically high level of productivity. This hints to a different channel operating over the firm size dimension, not present in the model so far. One promising idea is to introduce a screening motive similar to Helpman et al. (2010) explaining higher wages for large firms by higher average (unobserved) ability of workers which would also be in line with the lower job-filling rates for large firms.

Finally, I consider labor productivity and output. As z_H firms are on average larger, they more strongly face the decreasing returns to scale in the production function. Hence, the over 40% higher calibrated firm productivity y, only translates into an average labor productivity that is about 18% higher than their z_L counterparts. Due to the lower endogenous share of z_H firms in the economy, they account for one third of total output.



(a) Low-skilled **(b)** High-skilled

Figure 3.15: The figure shows average wages for both worker types by firm size and firm high-skilled share. All wages are relative to the average low-skilled wage in firms with a share below 20% in the largest size group.

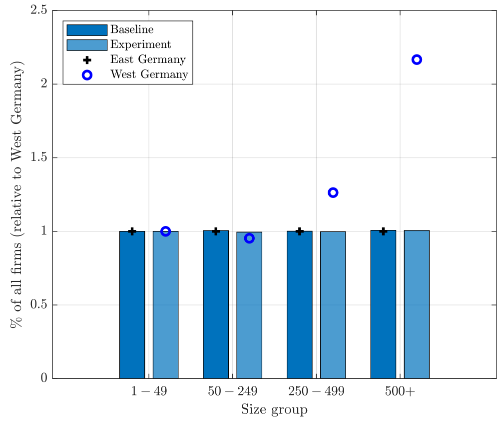
7 Experiment

This section contains the model experiment addressing the following guiding question: *How would have the East German economy looked like in 2015, if the relative supply of high-skilled workers had not diverged?* This experiment serves two purposes. First, I am interested in the effect of the change in relative labor supply on the firm distribution, on wages, as well as on productivity and its quantitative contribution towards observed differences between East and West Germany. Second, I view the implied changes in labor market outcomes as a way to gauge the external validity of the model: if the model response to the change in relative supply have the wrong sign or a counter-factual magnitude, this indicates a potential shortcoming of the model.

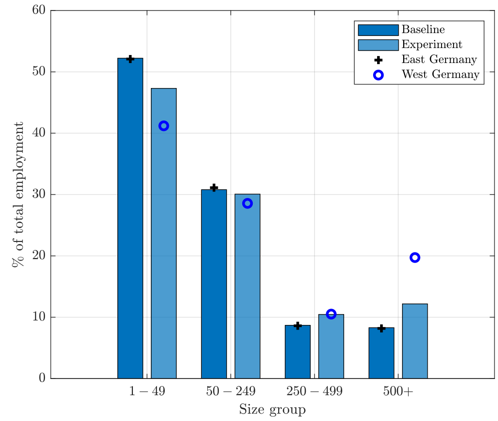
To implement this experiment, I change the share (and mass) of type H workers from 17.35% to 27.48% –the West German level in 2015– while fixing all other parameters at their calibrated values. Hence, I consider only the effect coming directly from the change in relative labor supply. While it seems natural that a change in relative labor supply has additional implications, for example West German firms might find it easier to hire high-skilled workers, I abstract from these effects in this experiment as there dependence on relative labor supply is unclear.[38] Therefore, the experiment is closely related to the exercise in Bachmann et al. (2022) where the authors calibrate the model to West Germany and exclusively change the wage-size function.

Due to the block recursive nature of the equilibrium, the increase in relative labor supply of high-skilled workers does not affect the policy functions of firms. In turn, this implies that all outcomes conditional on firm type are unchanged. However, the

[38]For example, I do not change the matching function parameters to their West German level, as they might be driven by different firm search behavior not necessarily related to the different relative labor supply.



(a) Firm shares



(b) Employment shares

Figure 3.16: The figure shows the firm and employment shares by firm size. For better visibility the firm shares are normalized by the East German level for each size bins.

change in labor supply does affect all (aggregate) equilibrium prices and allocations, since the firm distribution adjusts to satisfy the aggregate resource constraints. Since z_H firms account for a larger fraction of high-skilled workers and job-seekers, the increase in relative supply of those agents leads to a higher mass of those firms (from 0.03 to 0.09). At the same time, the relative (and due to the normalization absolute) supply of low-skilled workers decreases. Together with the larger mass of L-workers employed at z_H firms, this significantly reduces the mass of z_L firms (from 0.09 to 0.008). Hence, the model predicts an increase in the fraction of high-skilled intensive firms, qualitatively in line with the data. Albeit, the increase is quantitatively too large: for example, the firm-level average high-skilled share was about 22% in West Germany in 2015 while the model implies an average of about 30%. This is not surprising, as having only two firm types in the model are too few to capture the full extent of the high-skilled share dispersion within, and in particular for differences across, regions. Additionally, as mentioned in the beginning of the section, there might be other forces at work leading to a lower average skill share in West Germany compared to the model experiment.

Despite this shortcoming, the model's predictions regarding the firm size distributions seem plausible. As Figure 3.16b shows, firms in the counterfactual East Germany are on average larger in line with the data from West Germany. This is driven by the fact that with the larger relative supply of high-skilled workers, there are more high-skilled intensive firms which are larger. Regarding the firm shares in Figure 3.16, the model is calibrated to match the East German level. Since the decisions of firms do not change and since I imposed the same probabilities for drawing the permanent productivity levels across both firm types, the model cannot generate a different number of firms by size.[39] As firm shares are very similar across East and West Germany for the bottom two size groups, this circumstance does not matter much for these groups. However, the picture changes for firms with more than 250 employees. For those two size groups, West Germany features significantly more firms. Since the model is not calibrated to capture this feature, this circumstance impacts the models power to predict the employment shares for those large firms as discussed below.

Regarding employment shares, the experiment predicts a decline for the bottom two size groups and an increase for the top two size groups (Figure 3.16b) matching qualitatively the different employment distributions across Germany. Zooming in on the different size bins, the decline in the employment share of firm with less than 49 employees in the model accounts for 45% of the differences between East and West Germany. Moving to the second size group, the model explains about 28% of the observed differences. As the shares of firms in the first size group are nearly identical and differ with less than 5% for the second group between the regions, the calibration restriction that both firm types draw their productivities with the same probabilities has little effect for these two groups. The employment shares of firms with 250 to 499 employees in West Germany are nearly matched in the model explaining about 93% of the gap. However, as the model holds the firm shares by size constant, it does not account for the 26% higher number of firms in this size group in West Germany. Adjusting for the different firm shares, would likely yield an over prediction of the employment share of this group. Finally, turning to the largest firms, the higher relative supply is predicted to account for 34% of the employment differences. Interestingly, as the experiment implies a share that is nearly 50% of the West German level and West Germany featuring twice as many large firms as East Germany, accounting for the difference in the number of firms would close the gap completely.

The higher relative supply of high-skilled workers leading to larger firms has also implications for the size distribution over time. Starting from a (fictitious) 1995 calibration where the model would yield no effect on the size distribution as the relative supply of high-skilled workers is the same across regions, the steady increase in the high-skilled share over time in East Germany would be predicted to increase the employment share of large firms by the model. This is in line with the data from 1999 onward as depicted in Figure 3.24, after other reallocation effects (see Findeisen et al. (2021)) have vanished.

In summary, the experiment makes strong predictions regarding the firm size distribution, closing the gap between East and West Germany significantly, even though it does not account for the higher share of large firms in West Germany.

Turning to the effect on wages, Table 3.5 augments Table 3.1 from Section 3.4 with the estimated coefficients from the baseline model and the experiment. As discussed

[39]See Section 5 for more details.

	East Germany	Baseline Model	Experiment	West Germany
	Low-skilled wage			
High-skilled share	0.451	0.457	0.437	0.214
	(0.01)	(0.00007)	(0.0001)	(0.005)
Log firm size	0.077	-0.009	-0.012	0.069
	(0.001)	(0.000005)	(0.00001)	(0.0005)
	High-skilled wage			
High-skilled share	0.106	0.117	0.101	0.100
	(0.02)	(0.00003)	(0.00007)	(0.006)
Log firm size	0.095	-0.008	-0.008	0.055
	(0.003)	(0.000004)	(0.000006)	(0.0007)

Table 3.5: Regression results for estimating equation (3.3) for 2015. Additional control variables include dummies for gender, occupation, industry, as well as worker age, worker age squared and firm age in the data. For the model generated dataset, only firm age is included as a control variable. Standard errors in parenthesis. Data source: SIEED

in the previous section, the baseline model matches the semi-elasticity of the firm-level high-skilled share, but does not generate a positive wage size relationship. Regarding the effect of the higher relative supply of high-skilled workers, the experiment implies a lower wage-share semi-elasticity between the values for East and West Germany. While the relative change for low-skilled workers is minor, the parameter for high-skilled workers aligns with the observed coefficient for West Germany. Regarding the size-wage relationship, the elasticity is also decreasing. However, this has to be interpreted with caution, due to the aforementioned counterfactual near zero coefficient. Taken together, apart from the size-wage issue in the baseline calibration, the implications of the experiment are within expectations given the data.

Finally and most importantly, I consider the effects on aggregate wages and output. Table 3.6 compares relative changes between the baseline model and the experimental setting to relative differences between East and West Germany. As the table shows, the model implies a large increase in low-skilled wages of 5.6% which represents 25% of the low-skilled wage gap across the regions. For high-skilled workers, these numbers are significantly lower. High-skilled earn on average 1.1% more accounting for about 5.4% of their wage gap in the data. The reason for this differential effect is clear: low-skilled workers are estimated to benefit more from the composition within firms than high-skilled workers, while high-skilled workers profit stronger from working in larger firms. Since the first force is captured in the model, while the second is not, the model is more capable of explaining wage differences for low-skilled workers. This circumstance also explains the overshooting in the decline of the skill premium.

	Δ Experiment	Δ West Germany
$\bar{w}_L$	5.55%	22.51%
$\bar{w}_H$	1.05%	19.40%
$\bar{w}_H/\bar{w}_L$	-4.22%	-3.06%
$\bar{w}$	6.04%	23.23%
Y	5.31%	26.84%

Table 3.6: This table shows the main results of the experiment and compares them to the data. For the model, I compute the percentage change from the baseline calibration to the experimental setting with higher relative supply of high-skilled workers. For the data, I show the percentage difference between East Germany (basis) and West Germany. The data values for wages are the marginal effects from the regression of Section 3.3 controlling for worker and occupation characteristics. For output, the aggregate gap from national accounts are shown.

Overall, the model attributes 26% of the (conditional) wage gap to the lower relative supply of high-skilled workers in East Germany. This is in contrast to the 1.4% (contribution of 6.4%) increase in average wages from the mechanical effect of Section 3.3 ignoring any changes induced by the firm side (but controlling for compositional differences of workers and occupations). Regarding output, the experiment implies a 5.3% increase caused by the presence of more productive, high-skilled intensive firms. Since the data based on the IEB does not provide any output measures, I compare this figure to the aggregate output gap presented in Section 3.1. In relation to this gap, the model rationalizes about 20%. However, the model does not account for productivity differences caused by heterogeneity along other dimension like a different industry composition. In comparison, by studying differences caused by a differential size-wage relationship, Bachmann et al. (2022) rationalizes a drop in output and labor compensation of about 10 percentage points moving from West to East Germany.[40] While the effects in my model are smaller, they are economically meaningful and to a large extent complementary to the ones found in Bachmann et al. (2022) as my model does not yield any relationship between size and wages. A model combining both channels might be able to explain the majority of wage and output differences between East and West Germany.[41] In this light, the next section provides a discussion of possible extensions regarding the model and calibration.

[40] The estimates are not directly comparable as Bachmann et al. (2022) studies a pooled sample from 2006, 2010, and 2014.

[41] Note that with this experiment, the model would rationalize no observed differences for 1995 as the shares are identical. I expect the results to carry over for other years with contributions scaled by the difference in relative worker supply. However, a more serious calibration taking the time dimension into account as discussed in Section 7.1 might be more appropriate for this case.

7.1 Extensions

As briefly outlined before, the model as well as the experiment can be extended in multiple directions: First, while the previous exercise inspired by Bachmann et al. (2022) is interesting in itself, a more comprehensive calibration and experiment might yield more insights. If the model is calibrated to East and West Germany in 1995, the year featuring the same relative supply of workers, all differences between the two regions have to be driven by other forces, like differences in aggregate productivity. Then, feeding in the time series of relative labor supplies would allow to verify the external validity of the model further and to discriminate against other channels. However, this requires careful attention to related additional labor market trends and their interaction with the channels in the model. For example, as studied in Krebs and Scheffel (2013), the so-called Hartz reforms had a strong impact on the German labor market, affecting wages and transition rates.

Second, the model can be extended to endogenously link a higher firm-level share of high-skilled workers to larger, more productive firms in the spirit of Garicano and Rossi-Hansberg (2006). Currently, I assume that most of the heterogeneity in the composition of workers within firms is driven by exogenous differences in the output elasticity of worker types across firm types. In combination with higher vacancy posting costs for these firms, this leads to the observed positive relationship between the within firm composition and paid wages. However, without additional assumptions, the higher vacancy costs lead to a counter-factual small, negative relationship between firm size and wages. Additionally, as discussed in more detail in Section 6.1, the block-recursive nature of the model implies that the effects are driven by compositional effects between firm types and not by reactions in the policy functions of active firms. Endogenizing these relationships might yield further insides into the driver of the presented effects.

And finally, third, the model is efficient in the sense that a social planner would choose the same allocation given the labor market frictions and the exogenous labor supply. Hence, the model serves as a benchmark without any additional frictions or sources for inefficiencies, apart from the spatial friction between East and West Germany leading to misallocation across Germany. Depending on the aforementioned specification of the firms' production function, misallocation across firms within each region can be introduced setting the stage for policy intervention.

8 Conclusion

Why have average labor productivity and real wages not converged between East and West Germany after reunification? Inspired by the diverging relative supply of high-skilled workers, I propose a new explanation for this puzzle. East German firms facing a lower relative supply of high-skilled workers, operate with a different organization of production, stay smaller, are less productive, and pay lower wages. In this way, the lower relative labor supply of high-skilled workers contributes not only to the observed lower wages of high-skilled workers themselves, but also affect low-skilled workers, as well as productivity in East Germany.

To establish empirical evidence on this channel, I use three rich, administrative datasets containing information not only about the labor force in the economy but also about the composition within firms. This allows me to analyze the relationship between the organization of a firm, its size and wages. A decomposition of the wage gap between East and West Germany highlights the importance of low-skilled workers. At the same time, it implies only a small direct effect of the lower relative supply, in particular after controlling for worker and occupation characteristics. Turning to the workforce composition within firms, I find a positive relation between the size and the share of high-skilled workers in an establishment, as well as positive semi-elasticities regarding wages for both worker types and regions –in particular low-skilled in East Germany– controlling for observables including firm size. The estimated coefficient for low-skilled in East Germany implies a 8.6% higher wage when working for a firm with a one standard deviation higher share of high-skilled workers or up to a 7% higher wage for low-skilled workers in East Germany in a counterfactual world, where East Germany has the same labor force composition as West Germany.

To study the effects on productivity and to take the endogeneity of the firm distribution into account, I use the empirical results as input to a structural model to quantify the importance of this channel. I extend the directed search model with large firms from Kaas and Kircher (2015) by introducing ex-ante worker heterogeneity in the form of low and high-skilled workers as well as additional firm heterogeneity. Workers differ in terms of their productivity as well as in their labor market transitions and are both needed in the production process of firms. Firms types differ in their production function and in their vacancy posting cost function. This generates heterogeneity in the composition of the workforce among firms, a positive high-skilled share-wage relationship, and provides tractability as the model stays block-recursive.

Calibrating the model to East Germany in 2015 and changing the exogenous relative supply of high-skilled workers to the West German level, I estimate that 26% of the wage gap, after controlling for worker and job characteristics, between East and West Germany in 2015 can be explained by the different relative supply of workers. For the wage gaps conditional on worker skill, this number changes to about 25% for low-skilled and over 5% for high-skilled worker. Additionally, the model predicts a 20% smaller output gap.

These results have important implications for economic policy and policy in general. While the aggregate, direct effects of a diverging skill composition within East and West Germany are small, its effects operating via the firm distribution are substantial. In the presence of a continuation of the trend in relative worker supply overcoming productivity and wage inequality across Germany will be a difficult task. While multiple policies targeting firms in East Germany might come to mind, I argue that, for the long-term, primary focus should lie on educational outcomes, especially in the presence of a shortage of teachers.[42]

[42]In particular since the East German states feature the largest shares of old, soon-to-retire teachers among all federal states in Germany according to the Federal Bureau of Statistics.

Appendices

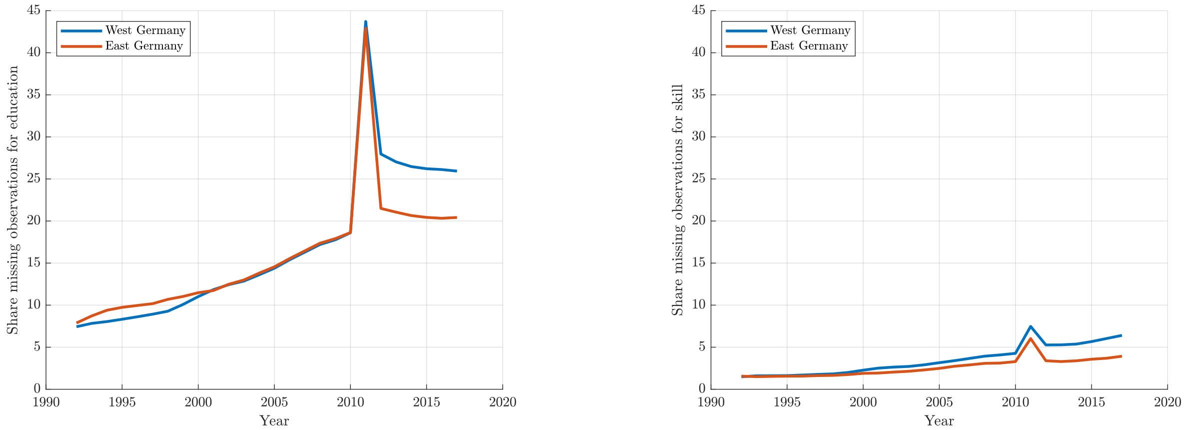
A Empirical Appendix

A.1 Number of Observations

	SIAB		SIEED				BHP	
	# of empl. workers		# of empl. workers		# of establishments		# of establishments	
Year	West	East	West	East	West	East	West	East
1993	290,991	55,914	208,786	44,897	16,461	3,570	615,461	124,521
1994	279,809	56,334	202,166	46,397	16,470	3,842	616,684	132,723
1995	276,298	56,914	202,677	46,078	16,515	3,947	620,424	138,463
1996	269,763	54,688	200,694	43,165	16,386	3,932	621,625	140,247
1997	264,680	52,223	196,346	42,899	16,378	3,945	619,308	139,918
1998	264,413	51,064	199,948	42,043	16,455	4,314	618,635	150,135
1999	265,778	50,147	203,439	41,202	16,768	4,396	773,803	164,101
2000	270,500	48,322	203,769	39,587	16,946	4,116	792,447	160,385
2001	270,179	45,937	205,870	37,457	16,888	3,924	792,473	155,076
2002	261,333	43,166	199,577	35,168	16,659	3,753	779,590	150,180
2003	252,811	41,970	192,456	33,768	16,212	3,608	776,140	148,747
2004	247,038	41,017	188,883	32,626	16,015	3,551	803,627	150,202
2005	242,186	39,596	186,016	31,404	15,728	3,390	815,898	147,125
2006	244,119	40,081	188,607	31,083	15,576	3,347	827,128	147,811
2007	248,913	41,403	195,700	32,463	15,715	3,415	837,531	149,337
2008	252,650	41,741	199,818	32,205	15,729	3,349	839,321	149,491
2009	243,343	40,303	193,779	31,571	15,514	3,248	844,146	149,537
2010	243,413	41,029	193,991	31,157	15,565	3,269	850,103	149,956
2011	233,114	38,896	189,278	30,515	14,976	3,106	856,564	150,185
2012	231,906	38,099	186,360	29,322	14,605	2,984	861,509	149,859
2013	233,703	37,929	188,775	29,967	14,566	2,944	864,337	148,947
2014	234,451	37,729	187,351	29,844	14,487	2,910	869,516	148,769
2015	236,723	37,257	190,649	29,272	14,404	2,833	869,762	147,021
2016	238,829	36,926	191,440	29,049	14,335	2,776	871,298	145,669
2017	240,368	36,710	194,928	28,704	14,304	2,703	872,061	144,447

Table 3.7: Number of observations by year and region in the final samples. For the SIEED the number of establishments with information about their whole workforce is reported.

A.2 Share of Missing Observations

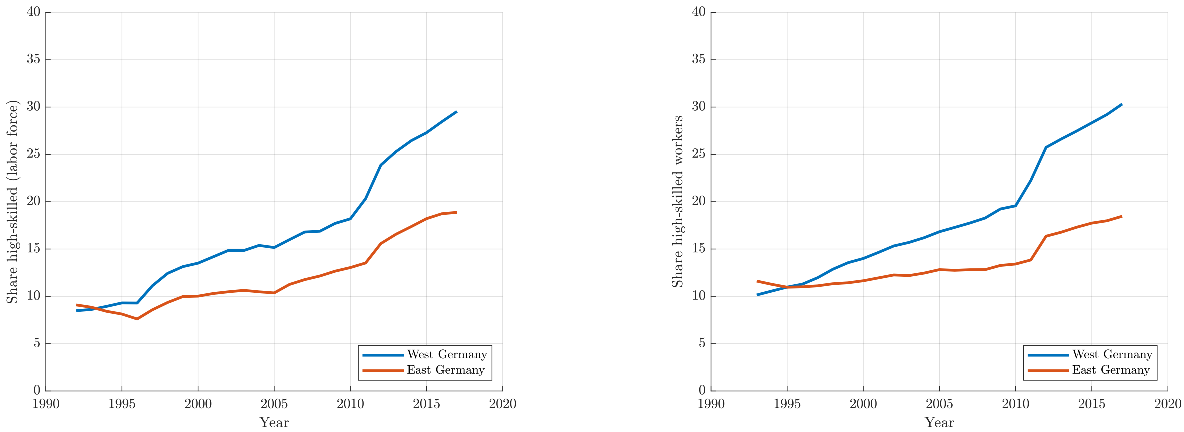


(a) Before imputation

(b) After imputation

Figure 3.17: The figure displays the share of missing observations for the school leaving qualification by region after construction of the sample. The left panel displays the share for the raw observations and the right panel the share after the imputation procedure. Data source: SIAB

A.3 High-Skilled Share Among the Labor Force



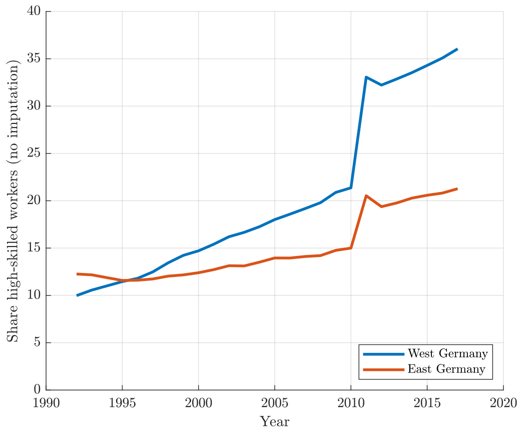
(a) All workers in sample (E+U)

(b) Employed

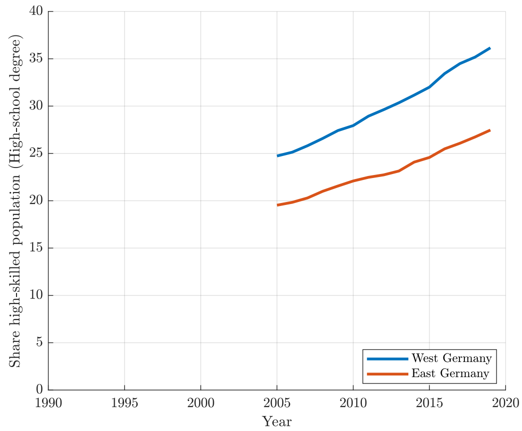
Figure 3.18: This figure depicts the share of high-skilled workers for East and West Germany over time. High-skilled workers are defined to have at least a high-school degree. See Section 2.4 for more details. Data source: SIAB

A.4 High-Skilled Share: Robustness

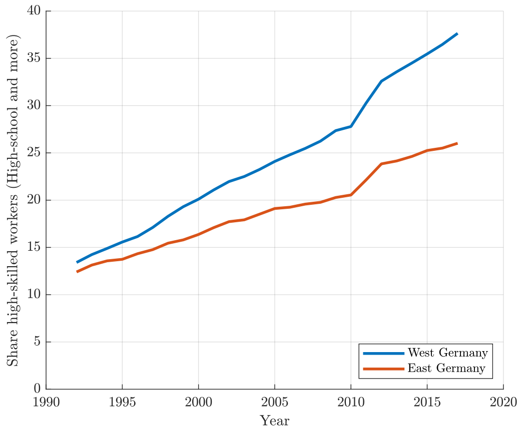
Figure 3.19 compares the high-skilled share implied by different samples and definitions. In particular, using the same definition of high-skilled and low-skilled, Figure 3.19b shows the high-skilled share in the micro-census, a 1% sample of all individuals living in Germany. Depending on the sample and definition, the level and the growth rate of the high-skilled share in East and West Germany varies. For the micro-census, this is caused by the different sample restrictions across the two datasets: the micro-census contains all individuals older than 15 years of age regardless of employment status, my SIAB sample includes only full-time employed, non-civil servants, between 16 and 60, working in the non-primary, private sector. As a consequence, two panels in the figure display a crossing point between the East and West German share before or shortly after 2000, the other two panels imply that the West German share was higher for all years after the reunification. However, all figures show a higher growth rate and, in the recent years, a higher level for the high-skilled share in West Germany, highlighting the robustness of the divergence in the share of high-skilled workers across the two regions. The high-skill share definition used in the main text implies a level and growth rate that is somewhere in between of the ones shown in the figure.



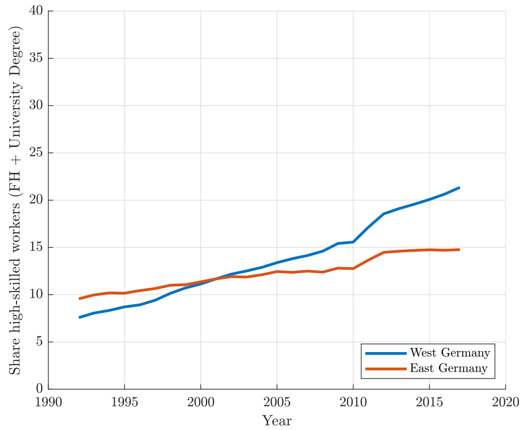
(a) No Imputation (SIAB)



(b) Micro-census



(c) At least High-school degree (SIAB)



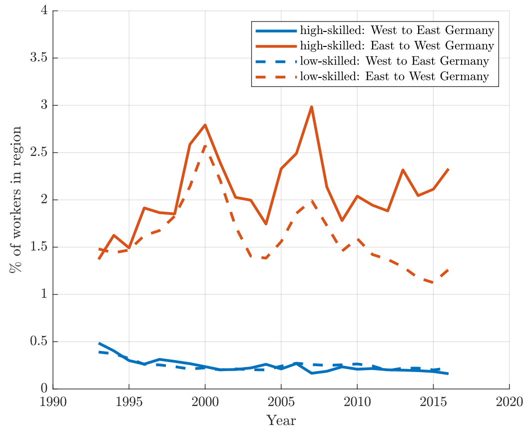
(d) FH and University degree (SIAB)

Figure 3.19: The figure shows the share of high-skilled workers for East and West Germany over time. The four panels display different datasets and high-skill definitions. Panel (a) show the high-skilled share defined as in the main text without the imputation procedure taking into account only individuals with information on their educational attainment. Panel (b) plots the share for the 1% sample of the Micro-census using the same definition. Panel (c) and (d) show the high-skilled share using the imputed variable *ausbildung imp* and different definitions. While Panel (c) illustrates the share of workers with at least a high-school degree, Panel (d) displays the share of workers with a University (of Applied Sciences) degree. Data sources: SIAB and Microcensus

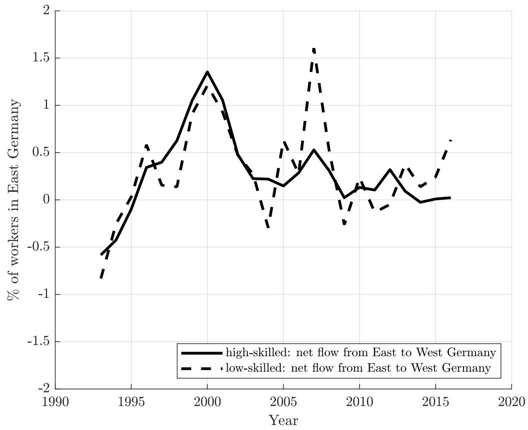
A.5 Role of Migration for the High-Skilled Share

As depicted in Figure 3.2 in Section 3.1, the share of high-skilled workers is increasing in East and West Germany over time with the latter region featuring a steeper incline. One explanation for this phenomenon are different migration patterns for low and high-skilled workers across the two regions. In particular, the lower increase in the high-skilled worker share for East Germany might be driven by lower net flows towards East Germany for high-skilled than for low-skilled.

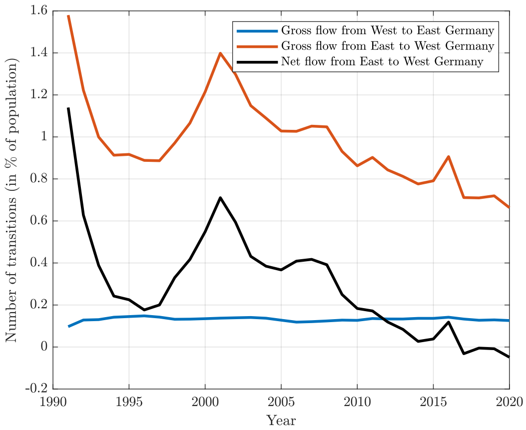
To verify this explanation, Figure 3.20 provides important pieces of information. First, Panel (c) displays the unconditional gross and net flows between East and West Germany over time from the Microcensus. Overall, many East German residents moved to West Germany, especially shortly after the German Reunification and in the early 2000s, the so-called ”first and second waves of migration”, respectively. During the whole period, there was a smaller, but meaningful gross flow of West Germans moving to East Germany. As the former gross flow is decreasing and the latter constant over time, net flows towards West Germany are declining with more people moving to than leaving East Germany in recent years. Panel (a) and (b) repeat this exercise conditioning on the two skill groups using the SIAB. In general, the migration patterns in the SIAB resemble the ones implied by the Microcensus, with the exception of a stronger ”third wave” around 2007. Regarding the skill groups, net flows mostly differ around the second and third wave. While relatively more high-skilled workers left East Germany during the second wave as documented in Fuchs-Schündeln and Schündeln (2009), larger migration from low-skilled are responsible for the spike around 2007. Overall, however, the net flows of the two skill groups are remarkably similar suggesting only a moderate effect on the high-skilled worker share over time. To gauge the effect, Panel (d) compares the evolution of the actual high-skilled worker share to counterfactual ones, where I subtracted the change in the share from migration, i.e., I assume that migration does not affect the high-skilled share. In line with Panel (c), the counterfactual share in East Germany starts to deviate during the second wave, but keeps the same gap over time. In 2016, without migration, the share differences between East and West Germany would be 10% smaller, confirming the minor role of migration.



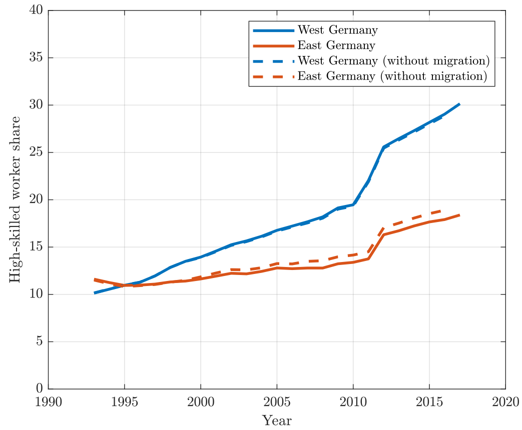
(a) Gross flows (SIAB)



(b) Net flows (SIAB)



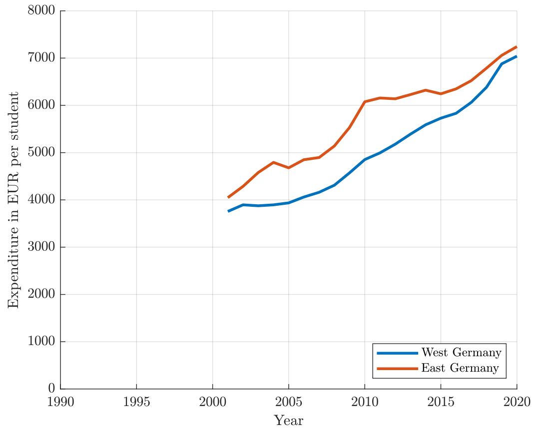
(c) Gross and net flows (Microcensus)



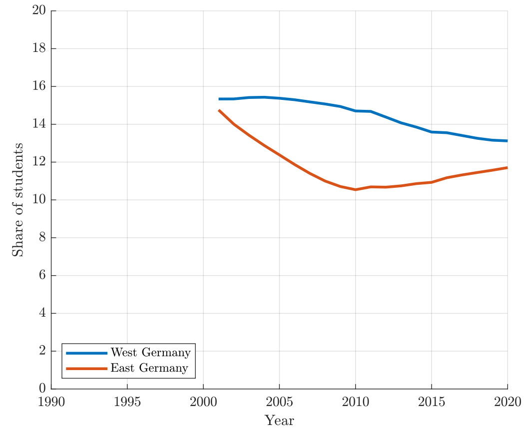
(d) Counterfactual high-skill share (SIAB)

Figure 3.20: The figure displays gross and net flows between East and West Germany over time and their impact on the high-skilled worker share. Panel (a) plots gross flows between the two regions by skill type. Panel (b) shows the analogous net flows to East Germany. Panel (c) depicts gross and net flows from the Microcensus. Panel (d) compares the high-skilled worker share from the main text to counterfactual shares without the effects from migration. Data source: SIAB and migration statistics (EVAS 12711-0022) from the Federal Bureau of Statistics

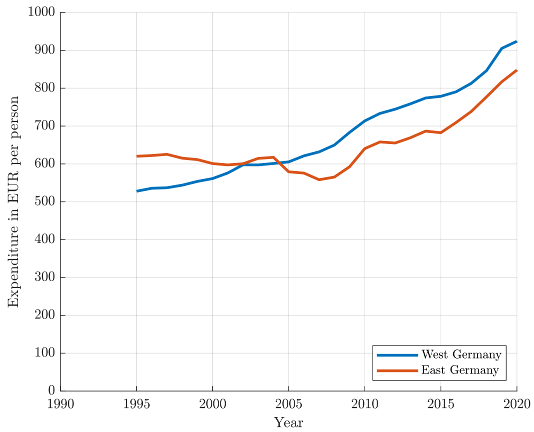
A.6 Education System: Expenditure and Participation



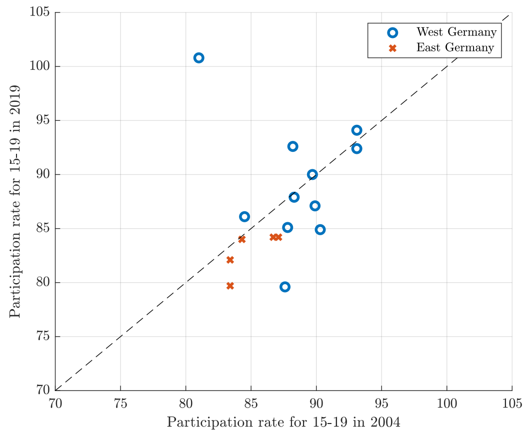
(a) Expenditure per student



(b) Share of students



(c) Expenditure per person



(d) Participation of 15-19 years old

Figure 3.21: The figure displays various statistics for the primary and secondary education system in East and West Germany. Panel (a) displays expenditures from the states and municipalities per student. Panel (b) plots the share of students in general and vocational schools among the population. Panel (c) shows expenditures per student and Panel (d) compares the share of 15 to 19 years old participating in the education system across time. Aggregated data source: Federal Statistical Office of Germany

A.7 Employment to Population by Education

State	< Upper secondary education ISCED 0–2	Upper & post-secondary non-tertiar education ISCED 3–4	All ISCED 0–8
Baden-Württemberg	70.1	84.7	84.3
Bavaria	70.9	84.6	84.8
Berlin	51.9	78.1	78.8
Brandenburg	66.2	83.2	82.4
Bremen	56.8	78.2	76.7
Hamburg	61.3	81.6	81.4
Hesse	61.8	81.7	80.7
Mecklenburg-Vorpommern	58.4	79.0	79.5
Lower Saxony	63.2	81.4	80.4
North Rhine-Westphalia	57.9	80.0	78.3
Rhineland-Palatinate	63.7	82.7	81.2
Saarland	63.0	79.4	79.5
Saxony	57.5	83.2	84.0
Saxony-Anhalt	58.8	81.1	80.8
Schleswig-Holstein	59.3	84.1	82.2
Thuringia	57.0	81.9	82.2
West Germany	62.7	82.2	81.5
East Germany	59.9	82.0	82.2

Table 3.8: This table shows the employment to population rate for 25-64 years old individuals in 2020 by state and education. ISCED: International Standard Classification of Education. Source: Microcensus

A.8 Average Wages: SIAB and VGR

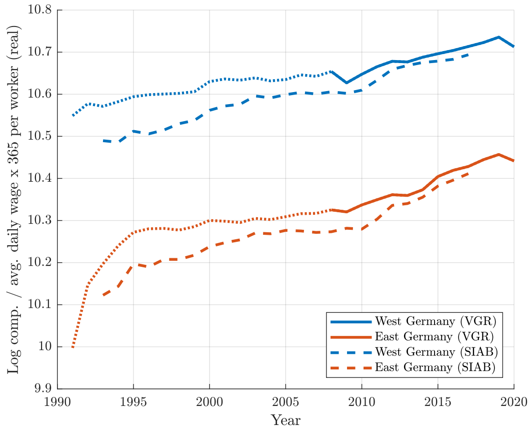


Figure 3.22: The figure compares the yearly log worker compensation from national accounts to the implied yearly log wages from the SIAB. All numbers are deflated. Data source: VGR/SIAB

A.9 High-Skilled Share Distribution by Industry and Region

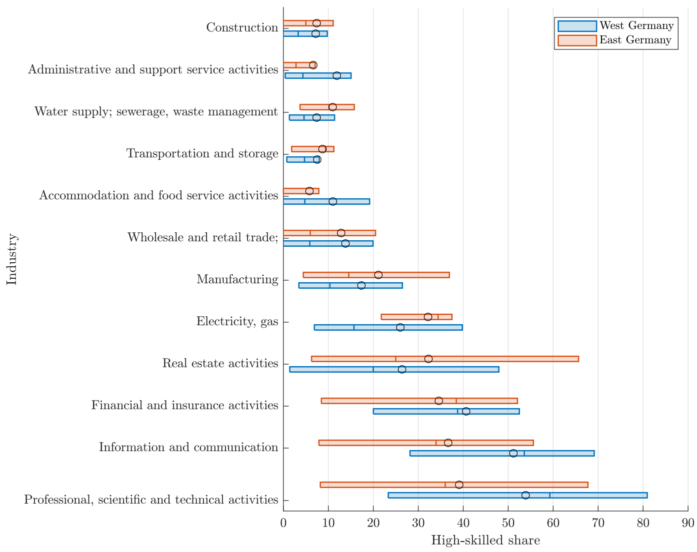


Figure 3.23: The figure shows the three quartiles and the mean of the employment weighted, within-firm high-skilled share distribution for different industries in East and West Germany. While the box represents the quartiles, the circles indicate the mean of the distribution. All years are pooled. Data source: SIEED

A.10 Regressions of Firm Characteristics on High-Skilled Share

high-skilled worker share in %	All years pooled	2015
log(size)	1.218***	1.824***
	(0.030)	(0.188)
firm age	−0.032***	−0.148***
	(0.004)	(0.019)
East	−1.207***	−5.032***
	(0.095)	(0.598)
Industry		
Electricity, gas	7.672***	6.121*
	(0.601)	(3.229)
Water supply; sewerage, waste management	−0.066	−3.447
	(0.468)	(2.726)
Construction	−4.207***	−7.042***
	(0.128)	(0.819)
Wholesale and retail trade	1.917***	3.088***
	(0.116)	(0.750)
Transportation and storage	−3.503***	−5.442***
	(0.174)	(1.113)
Accommodation and food service activities	−3.044***	−3.413***
	(0.157)	(1.030)
Information and communication	34.944***	45.828***
	(0.230)	(1.291)
Financial and insurance activities	17.811***	28.612***
	(0.222)	(1.379)
Real estate activities	9.920***	17.105***
	(0.243)	(1.511)
Professional, scientific and technical activities	28.467***	38.083***
	(0.142)	(0.888)
Administrative and support service activities	2.912***	4.407***
	(0.175)	(1.030)
constant	7.025***	14.486***
	(0.119)	(0.777)
N	480,829	17,237
R^2	0.1722	0.2414

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.9: Regression results of regressing firm characteristics on the high-skilled worker share within a firm for different samples. The baseline is *Manufacturing* in West Germany. Standard errors are in parenthesis.

A.11 Firm Size

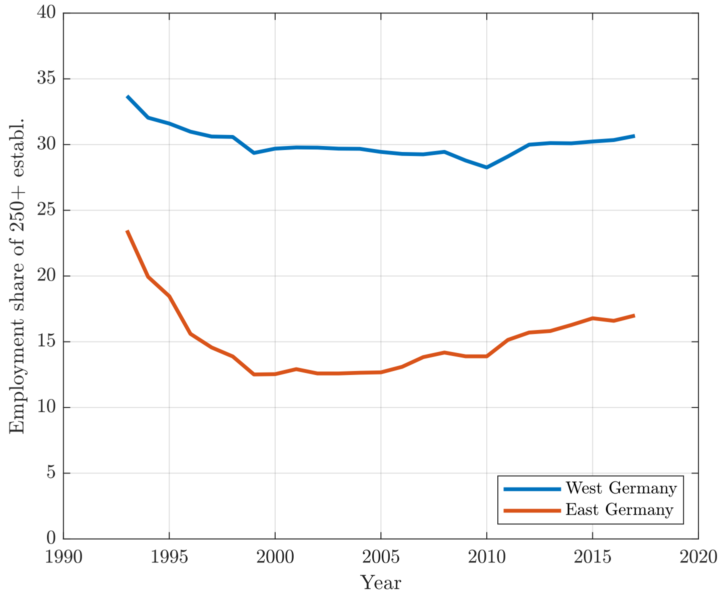
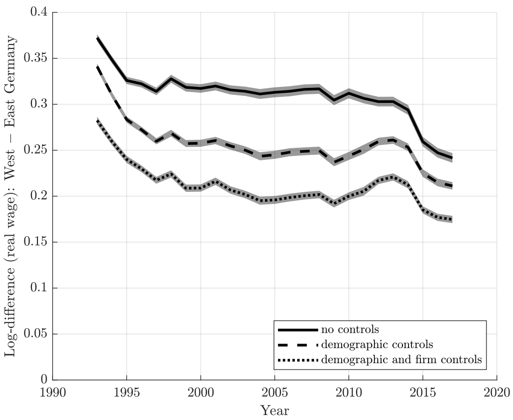
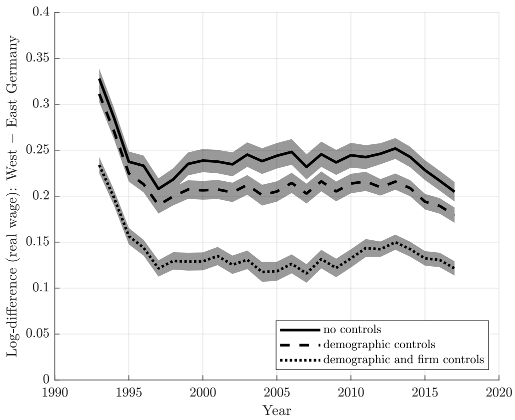


Figure 3.24: The figure shows the employment share of establishments with at least 250 employees. Data source: BHP

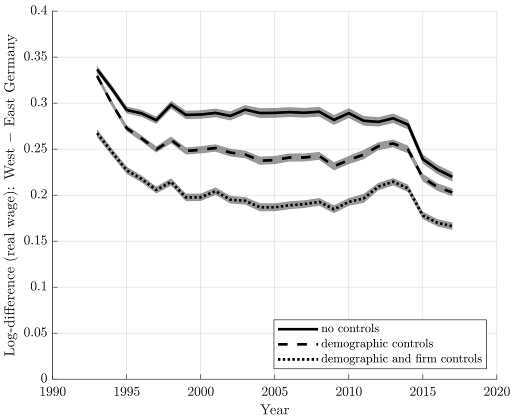
A.12 Robustness of Estimated Wage Gaps by Skill



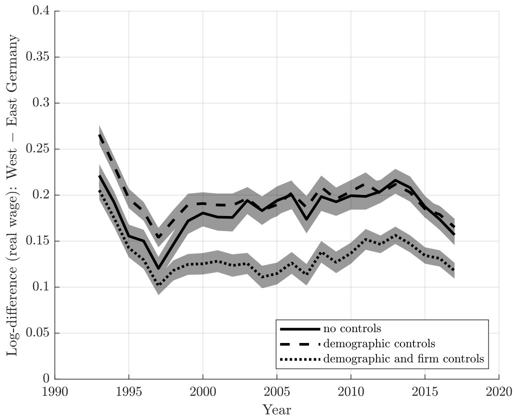
(a) Low-skilled (baseline)



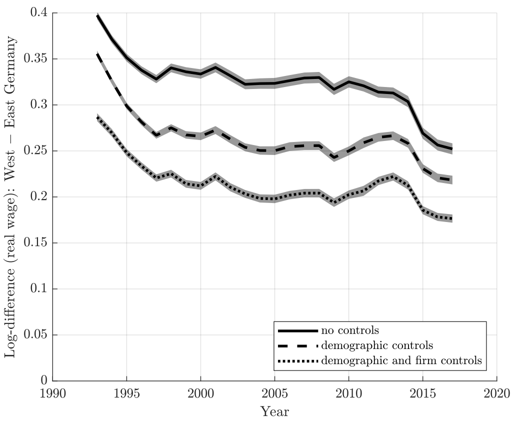
(b) High-skilled (baseline)



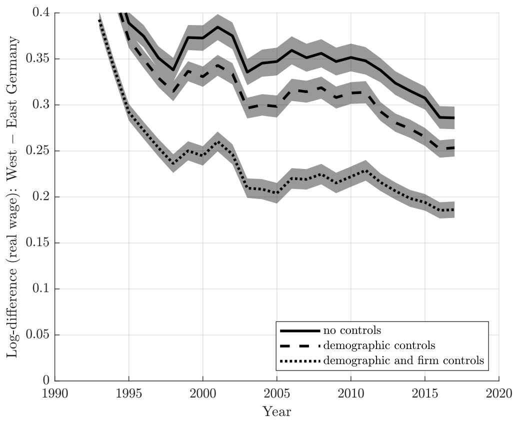
(c) Low-skilled (no censored)



(d) High-skilled (no censored)



(e) Low-skilled (imputed)

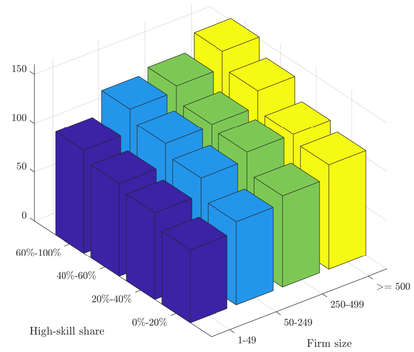


(f) High-skilled (imputed)

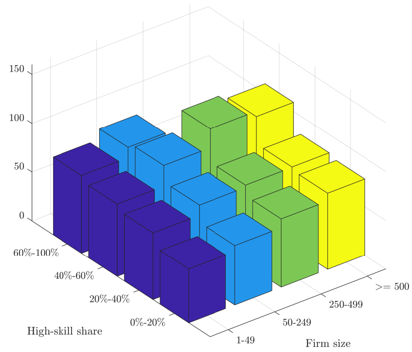
Figure 3.25: The two panels show the estimated East-West German wage gap for low-skilled (left panel) and for high skilled (right-panel) for three different specifications: unconditional, conditional on worker and job characteristics, and additionally conditional on firm characteristics. The gaps are defined as β_w and $\beta_w + \beta_{wh}$ from equation (3.2). Shaded areas represent 95% confidence intervals. **no censored:** only wages below 4€ below the contribution limit. **imputed:** impute censored wages following Dauth and Eppelsheimer (2020). Data source: SIAB

A.13 Average Wages by Firm Size and High-Skilled Share

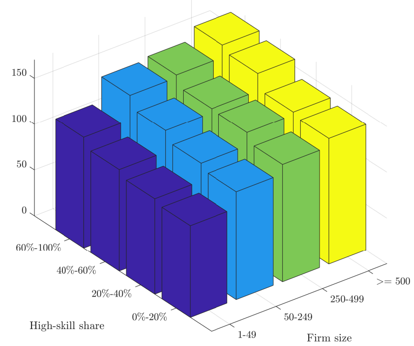
Figure 3.26 illustrate the average wage for low and high-skilled workers by establishment size and high-skilled share. For West Germany and for both worker types, a comparable wage gradient between establishment size and the high-skilled worker share given the definition of the bins can be observed. The largest establishments with the highest share pay the highest average wages for both worker types. The picture for East Germany is less clear. This is mostly due to the fact that there are few large establishments and very few establishments with a high share in the sample. However, regarding only the lowest three share bins, leads to a similar wage gradient regarding the establishment level share, and the low incline in average wages by firm size, as documented in Bachmann et al. (2022).



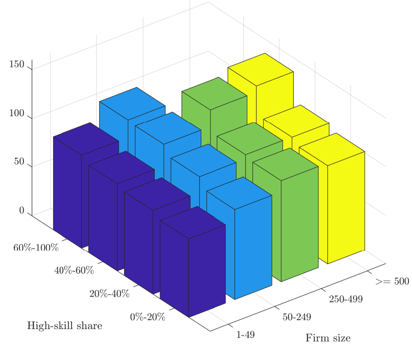
(a) Low-skilled, West Germany



(b) Low-skilled, East Germany



(c) High-skilled, West Germany



(d) High-skilled, East Germany

Figure 3.26: This figure shows average of low and high-skilled workers by establishment size and establishment-level high-skilled worker share. Average wages are weighted by the number of low and high-skilled workers in an establishment, respectively. Two bars for East Germany are not visible due to insufficient observations. All years are pooled. Data source: SIEED

A.14 Wage – High-Skilled Share Regressions

	Low-skilled wage		High-skilled wage	
	West Germany	East Germany	West Germany	East Germany
High-skilled share	0.304***	0.472***	0.085***	0.150***
	(0.001)	(0.001)	(0.017)	(0.004)
Log firm size	0.065***	0.069***	0.058***	0.085***
	(0.0001)	(0.00009)	(0.00003)	(0.0002)
firm age	0.001***	0.001***	−0.0008***	−0.0004*
	(0.00001)	(0.00009)	(0.00003)	(0.0002)
worker age	0.032***	0.031***	0.068***	0.056***
	(0.0001)	(0.0003)	(0.0003)	(0.0008)
worker age squared	−0.0003***	−0.0003***	−0.0007***	−0.0006***
	(0.000001)	(0.000003)	(0.000003)	(0.000009)
female	−0.271***	−0.197***	−0.138***	−0.143***
	(0.0005)	(0.001)	(0.0008)	(0.002)
constant	3.343***	2.964***	2.871***	2.683***
	(0.018)	(0.0333)	(0.035)	(0.073)
# of occupations	342	330	328	286
# of industries	12	12	12	12
# of years	25	25	25	25
N	3,915,249	744,096	936,427	129,513
R^2	0.5016	0.4872	0.4902	0.4667

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3.10: Regression results for estimating equation (3.3). Standard errors are in parenthesis. Data source: SIEED

	Low-skilled wage		High-skilled wage	
	West Germany	East Germany	West Germany	East Germany
High-skilled share	0.2751***	0.4447***	0.07061***	0.0954***
	(0.0014)	(0.0034)	(0.0022)	(0.0055)
Log firm size	0.0660***	0.0673***	0.0651365***	0.0857***
	(0.0001)	(0.0003)	(0.0002463)	(0.0008)
firm age	0.0016***	0.0010***	−0.0004161***	−0.00009
	(0.00002)	(0.00009)	(0.0000446)	(0.0003)
worker age	0.0312***	0.0300***	0.0644951***	0.0482***
	(0.0001)	(0.0003)	(0.0004097)	(0.0010)
worker age squared	−0.0003***	−0.0003***	−0.0007133***	−0.0005***
	(0.000001)	(0.000003)	(0.000005)	(0.00001)
female	−0.2498***	−0.1812***	−0.1166261***	−0.1242***
	(0.0005)	(0.0011)	(0.0010555)	(0.0026)
constant	3.3635***	2.9883***	2.83716***	2.9041***
	(0.0174)	(0.0327)	(0.04988)	(0.0776)
# of occupations	342	330	325	286
# of industries	12	12	12	12
# of years	25	25	25	25
N	3,680,484	727,984	579,461	91,049
R^2	0.4652	0.4688	0.3930	0.3728

Notes: * $p < 0.01$; ** $p < 0.005$; *** $p < 0.001$

Table 3.11: Regression results for estimating equation (3.3). Standard errors are in parenthesis. **Excluding wages above 4€ below the contribution limit**. Data source: SIEED

	Low-skilled wage		High-skilled wage	
	West Germany	East Germany	West Germany	East Germany
High-skilled share	0.3484***	0.4983***	0.1927***	0.3006***
	(0.0014)	(0.0032)	(0.0024)	(0.0055)
Log firm size	0.0686***	0.0703***	0.0905***	0.1148***
	(0.0001	(0.0002)	(0.0003)	(0.0007)
firm age	0.0014***	0.0010***	−0.0013***	0.0009**
	(0.00002)	(0.00008)	(0.00004)	(0.0003)
worker age	0.0327***	0.0311***	0.0919***	0.0699***
	(0.0001)	(0.0003)	(0.0004)	(0.0010)
worker age squared	−0.0003***	−0.0003***	−0.0009***	−0.0007***
	(0.000002)	(0.000003)	(0.000005)	(0.00001)
female	−0.2906***	−0.2020***	−0.2191***	−0.1894***
	(0.0005)	(0.0010)	(0.0012)	(0.0026)
constant	3.3127***	2.9259***	2.2555***	2.1249***
	(0.0179)	(0.0324)	(0.0522)	(0.0896)
# of occupations	342	330	328	286
# of industries	12	12	12	12
# of years	25	25	25	25
N	3,911,723	743,607	935,696	129,434
R^2	0.5248	0.5146	0.4992	0.5056

Notes: * $p < 0.01$; ** $p < 0.005$; *** $p < 0.001$

Table 3.12: Regression results for estimating equation (3.3). Standard errors are in parenthesis. **Imputed wages above 4€ below the contribution limit following Dauth and Eppelsheimer (2020)**. Data source: SIEED

B Model and Computational Appendix

B.1 Problem for the Firm

This section presents the firm problem arising from Section 4.1 to 4.4, closely mirroring Schaal (2017) with some notable changes: heterogeneous worker productivities, non-linear vacancy costs, no on-the-job search, and no idiosyncratic or aggregate uncertainty.

Consider a firm with productivity y and type z which currently employs (n_L, n_H) workers. Let the j-th worker of type x_i be denoted by (j, i). For each worker the firm needs to keep track of the (remaining) promised value $W_{(j,i)}$. The firm's problem is twofold: first, it must re-design the contracts for all existing workers

$$\mathfrak{C}_{(j,i)} = \left\{ w_{(j,i)}, s_{(j,i)}(y,z), \delta(y,z), W'_{(j,i)}(y,z) \right\} \forall j \in [0, n_i] \quad i \in \{L, H\}$$

This includes an exiting probability for the firm, as well as a separation probability and wage schedule on an individual worker level. Second, it must choose the number of vacancies for next period (V_L, V_H) as well as the corresponding promised value (W_L, W_H). Therefore, the value function of a firm at the production stage is given by

$$J\left(y, z, n_L, n_H, \left\{W_{(j,i)}\right\}\right) = \max_{\{\mathfrak{C}_{(j,i)}\},\{V_i, W_i\}} F(y, z, n_L, n_H) - f - \sum_{i \in \{L,H\}} \int_{j=0}^{n_i} w_{(j,i)} dj$$
$$+ \beta \mathbb{E}\left[-C(V_L, V_H, n_L, n_H, z) + J\left(y, z, n_L, n_H, \left\{\hat{W}_{(j',i)}\right\}\right)\right]^+ \tag{3.1}$$

subject to

$$h'_i = m(W_i, x_i) v_i \tag{3.2}$$
$$n'_i = \int_0^{n_i} (1 - s_{(j,i)}) dj + h'_i \tag{3.3}$$
$$\hat{W}_{(j',i)} = \begin{cases} W'_{(j',i)} & j' \in [0, n'_i - h'_i], j' = \Phi(y, x_i; j) \\ W_i & j' \in [n'_i - h'_i, n'_i] \end{cases} \tag{3.4}$$
$$W_{(j,i)} \leq W(y, x_i, \mathfrak{C}_{(j,i)}) \quad \forall j \in [0, n_i] \forall i \tag{3.5}$$

where $(\cdot)^+$ is defined as $\max(\cdot, 0)$ incorporating the exit decision δ and the function

$$\Phi(y, x_i; j) = \int_0^j (1 - s_{(k,i)}) dk \tag{3.6}$$

re-indexes the existing workforce.

While the constraints (3.2) and (3.3) follow naturally from the fact that future employment is the sum of remaining workers and newly hired workers, the additional constants are more complicated. (3.4) assigns the new promised value to workers depending on their previous labor market status: if they were previously employed by the firm, then their promised value gets re-optimized according to the new contract. If they are newly hired, they get the promised value offered during hiring. The last constraint, the promise-keeping constraint (3.5), requires that the remaining value assigned to previously hired workers in combination with the wage and the separation probability cannot be lower than the previously promised value.

Following Schaal (2017) allows me to simplify the firm's problem considerably. Schaal (2017) proves that due to the completeness of contracts, commitment, and transferability of utility, this problem is equivalent to first optimizing the sum of the values of all workers at the firm and the firm's value and then, second, solving for the contracts that implement the allocation, e.g., the wage schedules and separation probabilities.

B.2 Computation of Equilibrium

Solving for the equilibrium is computationally expensive, even in the presence of a block-recursive model. The main complication arises due to the fact that the multi-dimensional firm problem has to be solved many times and cannot be transformed to a series of one-dimensional problems as the production function introduces complementarities between workers. Furthermore, the hiring vis-à-vis firing decision introduces a kink in the objective function. In this section, I lay out the algorithm and discuss steps to alleviate this issue. The general idea of the algorithm is the following:

1. Guess $U(x)$ (or equivalently $\rho(x)$) for each x.

2. Given $U(x)$, the firm knows the trade-off between m and W for each worker type.
   Solve the firm's joint surplus maximization problem and compute the expected value of entering for each type z.

3. Iterate over $U(x)$ until the expected value of entering aligns with the entry costs $K(z)$.

4. Solve for the firm distribution for each firm type z and compute the implied mass of entrants for each type.

5. Using the firm distribution, compute the implied share of high-skilled workers for each firm type z. Use the implied share to compute the total mass of firms of each type such that the aggregate resource constraint holds.

6. Compute the flat wage schedule.

First, in Step 2, the model is solved by value function iteration (VFI) with 120 exponentially spaced grid points in each workforce dimension.Using VFI is significantly slower than other methods but is robust enough to handle the kinks in the objective function. To increase performance, I solve and simulate the model in C++. The location of the grid points is chosen in a way to obtain enough precision for entering firms with a very small workforce while still providing enough resolution for firms close to their steady state workforce. Additionally, it is convenient to consider the worker-firm optimization problem at the beginning of the period after the productivity shocks have realized as discussed in the appendix of Schaal (2017). The joint surplus at the beginning of the period is given by

$$\begin{aligned} JS^A(y,z,n_L,n_H) = & \max_{\delta,V_L,V_H,W_L,W_H,s_L,s_H} \delta \sum_{i\in\{L,H\}} n_i U(x_i) \\ & + (1-\delta)\Bigg[\sum_{i\in\{L,H\}} n_i s_i U(x_i) - C(V_L,V_H,n_L,n_H,y,z) \\ & - \sum_{i\in\{L,H\}} m(W_i,x_i)V_iW_i + F(y,z,n'_L,n'_H) - f + \beta\mathbb{E}[JS^A(y,z,n'_L,n'_H)]\Bigg] \end{aligned} \tag{3.7}$$

subject to

$$n'_i = n_i(1-s_i) + m(W_i,x_i)V_i \quad i \in \{L,H\}$$

as well as the relationship between W and m which avoids the dependence of the decision on future productivity. To relate the free entry condition to JS^A instead of JS, it needs to be adjusted to

$$\begin{aligned} K(z) = & \sum_y g_y(y) \max_{V^e_L,V^e_H,W^e_L,W^e_H,\delta^e} (1-\delta^e) \\ & \times \Bigg[F(y,z,n_L,n_H) - f - C(V^e_L,V^e_H,0,0,y,z) - \sum_{i\in\{L,H\}} n^e_i W^e_i + \beta\mathbb{E}[JS^A(y,z,n^e_L,n^e_H)]\Bigg] \end{aligned} \tag{3.8}$$

with

$$n^e_i = m(W^e_i,x_i)V^e_i \quad i \in \{L,H\}.$$

Moreover, I reformulate the problem in terms of future employment and solve for the optimal implementation of hirings before the value function iteration.

The computation of wages in Step 6 is discussed below. As in most labor market models with directed search, wages are not uniquely pinned down without further assumptions. I follow Kaas and Kircher (2015) and assume a "flat" wage schedule, i.e, that wages are constant over the employment relationship with the firm for a worker. Note that due to the assumption that a firm hires a worker in the middle of the period before production, an employed worker has to consider the future state of the firm to evaluate her separation probability. This assumption allows a simple computation of wages in line with Kaas and Kircher (2015). To obtain a concise formula for wages, consider the following set of equations implied by (3.4) and (3.5)

$$\begin{aligned} W(w,x,y,z,n_L,n_H) &= w(x) + \beta \mathbb{E}\left[(1-\varphi(x,y,z,n_L',n_H'))U(x)\right. \\ &\qquad \left. + \varphi(x,y,z,n_L',n_H')W(w,x,y,z,n_L',n_H')\right] \\ \rho(x) &= \beta \frac{m(x,y,z,n_L,n_H)}{\lambda(m(x,y,z,n_L,n_H))}[W(w,x,y,z,n_L,n_H) - U(x)] \\ U(x) &= b(x) + \rho(x) + \beta U(x) \end{aligned}$$

Subtracting the third equation from the first, results in

$$\begin{aligned} \underbrace{W(w,x,y,z,n_L,n_H) - U(x)}_{Z:=} &= w(x) - b(x) - \rho(x) \\ &\qquad + \beta \mathbb{E}[\varphi(x,y,z,n_L',n_H')\underbrace{(W(w,x,y,z,n_L',n_H') - U(x))}_{Z'=}] \end{aligned}$$

with

$$Z = A(x,y,z,n_L,n_H)(w(x) - b(x) - \rho(x))$$

and A, in turn, is the solution to

$$A(x,y,z,n_L,n_H) = 1 + \beta \mathbb{E}[\varphi(x,y,z,n_L',n_H')A(x,y,z,n_L',n_H')].$$

Replacing Z in the second equation above, the following wage equation is obtained

$$w^*(x,y,z,n_L,n_H) = b(x) + \rho(x) + \frac{1}{\beta}\rho(x)\frac{\lambda(m(x,y,z,n_L,n_H))}{m(x,y,z,n_L,n_H)}\frac{1}{A(x,y,z,n_L,n_H)}.$$

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