Essays on Individual Labor Income Dynamics

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To Ann-Kathrin

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Chapter 1

Introduction

This thesis consists of four self-contained chapters that are linked by the common topic of individual labor income dynamics. For most households labor income is the main source of income. This implies that it matters for many decisions of these households how their labor incomes change over time: they save to cover the expenditures triggered by unforeseen events or to bridge periods of unemployment; they invest in education partly in expectation of higher incomes in the future; even fertility decisions can be affected if the future income stream is highly risky from the perspective of the households.

More specific, this thesis covers two aspects of labor income. First, it explicitly decomposes observed income dynamics into components of risk on the one hand and choice on the other. Second, it analyzes the dynamics of labor incomes over the business cycle and asks how well households can insure themselves against cyclical fluctuations of the main earner's income and how well the government provides additional insurance via the existing tax and transfer system.

The literature on labor income risk usually treats the wage process as exogenous to workers, with few exceptions. Those papers study labor income risk by analyzing data on labor income and treat the income changes as "shocks", after controlling for some observable characteristics like age and gender (prominent examples are Moffitt and Gottschalk, 2002, or Guvenen, 2009). However, observed wage dynamics are the result of both exogenous factors, such as productivity shocks, and workers' choices. In Chapter 2, I analyze the relationship between the decision of workers to switch occupations and the dynamics of labor income. I focus on the choice to switch occupations for two reasons. First, the extent of occupational switching upon changing establishments is high, as I document using data from administrative German social security records: on average 40% of workers who change establishments also change occupation (in a classification with 30 occupational groups). Second, the decision to change occupations is of major relevance for realized wages: in terms of the log 90–10 differential, the distribution of wage changes is about 60% wider for workers that switch occupations than for workers that change establishments within their occupation (for workers that experience an unemployment spell, the distribution is 30% wider).

I then develop a structural model in which workers optimally choose occupations in response to productivity shocks. This choice then also affects their accumulation of human capital, which is imperfectly transferable across occupations. The observed productivity changes of workers in the model economy differ from the underlying productivity shocks. This distinction allows me to use the model to (i) identify the role of occupational switching choices for productivity changes and (ii) to quantify the utility gain from the option of occupational switching. The model is calibrated to be consistent with the occupational and wage dynamics documented in the data. In the calibrated model, the endogenous choice of occupations accounts for 26% of the dispersion of idiosyncratic productivity changes after controlling for human capital changes. The utility gain from the availability of switching occupations corresponds to about 0.78% of per-period consumption for the average worker. This gain reflects that a worker, looking into the future, knows that some shocks he receives will be connected to his current occupation and by leaving for another occupation he can mitigate these negative shocks to some extent. At the same time, some high positive income changes are related to switching occupations in the context of career progression.

The focus of the analysis here is on uncovering underlying risk and the role of occupational choice as a device for workers to react in part to this underlying risk. Given this connection, the model framework now allows to think about the role for wage dynamics of policies that affect the incentives to switch occupations. This normative analysis is left for future research.

Chapters 3 and 4 both evolve around the question how labor incomes vary over the business cycle. Chapter 3 covers a joint paper with Alexander Ludwig. We analyze the income streams realized by households and ask if and how the distribution of income shocks across individuals varies systematically over the business cycle, where "shocks" refers to income changes. In more technical terms, we develop a novel parametric approach to estimate the relationship between idiosyncratic and aggregate labor income risk. This connection has been shown in the literature to have potentially important implications for macroeconomic phenomena, e.g., for asset pricing (e.g., Storesletten et al., 2007) or the welfare costs of business cycles (e.g., Storesletten et al., 2001a, or Lucas, 2003).

Early evidence by Storesletten et al. (2004) suggests that in a classic decomposition of income changes into transitory and permanent shocks (cf., Moffitt and Gottschalk, 2002) the variance of the permanent component is larger in recessions than in booms. More recently, Guvenen et al. (2014) report that the variance of shocks does not change over the business cycle, but that instead the distribution becomes more negatively skewed, which means that the distribution varies asymmetrically and downside risk becomes larger in recessions. However, their analysis is non-parametric and thus the results are not directly comparable to Storesletten et al. (2004). The analysis in chapter 3 fills this gap by providing identification for the cyclicality of the skewness of permanent shocks.

In a nutshell, the idea is that long-lasting income changes accumulate over time. If the distribution of these changes varies systematically between aggregate contractions and expansions, then the cross-sectional distribution of incomes of a cohort of workers that went through more *bad times* will differ from the cross-sectional distribution of another cohort at the same age. This idea was brought forward by Storesletten et al. (2004), who allow the *variance* of the shocks to take on different values in recessions and booms. We extend their analysis and show that the general idea carries over to the *skewness* of the distribution, a measure of its (a)symmetry. We derive closed form expressions for the cross-sectional variance and skewness of income, and achieve identification of the corresponding moments of the shocks in a Generalized Method of Moments (GMM) framework.

Applying our method to German data from the Socioeconomic Panel Study, we find that the variance of permanent shocks to gross labor earnings of males increases in recessions. This is in line with the results of Storesletten et al. (2004). However, we find that this increase of the variance is asymmetric–which is reflected in the estimation by a procyclical skewness of the permanent shocks. Together, the increase of the variance together with a more left-skewed distribution in aggregate contractions indicates that negative log earnings realizations become relatively more likely than positive ones in economic downturns. We then estimate the stochastic process for labor incomes at the household level: for household gross labor earnings we find insurance against transitory but not against permanent shocks. "Insurance" is meant here in the sense that transitory shocks are less dispersed and less negatively skewed for households than for individuals. Finally, the German tax and transfer system provides insurance against both shocks: when considering taxes and transfers and estimating the process for a measure of post-government household income the cyclicality of household labor earnings risk is gone.

Chapter 4 covers a joint paper with David Domeij, Fatih Guvenen, and Rocio Madera.[1]

[1] In terms of the relative contributions, the whole project was joint work in the sense that the substantial decisions were made jointly in an iterative process. The different contributions then mainly concern the data preparation and application, in my specific case the SOEP and the SIAB data. Further, the application in the structural model and the programming of the Simulated Method of Moments estimator

Relative to the previous chapter, the analysis mainly differs along two dimensions. First, it zooms out and provides a comparative analysis of the United States, Germany, and Sweden. Second, it differs from a methodological point of view, because we do not impose any parametric structure on the distribution of income shocks. Instead, we use non-parametric methods to analyze the cyclical behavior of labor income changes, the role of household insurance against this cyclical risk, and the effectiveness of government insurance schemes. We find that across the different labor markets, individual labor income risk behaves similar and that households are exposed to almost the same risk as individuals. Namely, downside risk is higher in recessions. The existing tax and transfer schedules are successful at reducing the asymmetric risk in all three economies. The chapter finishes with an evaluation of the welfare gain coming from the insurance provided by the government on top of within-household insurance. To this end, we adopt an incomplete markets model with partial insurance of households against fluctuations developed by Heathcote et al. (2014). Households in the model face an exogenous income process that we estimate separately for each economy and for pre- and post-government household income. We find the gain to be highest in Sweden, followed by the United States and Germany.

Chapter 5 again deals with the question of how labor incomes vary over the business cycle. Compared to the two preceding chapters, it takes a more structural perspective and discusses a specific channel through which workers are affected asymmetrically by aggregate fluctuations. The goal of the chapter is to evaluate the welfare costs of aggregate fluctuations in the presence of imperfect mobility of workers across sectos. To this end, I set up a real business cycle model with two production sectors and involuntary unemployment. An important feature of the model is that aggregate fluctuations are endogenously propagated asymmetrically to the two sectors–and as a consequence, workers want to move across sectors in response to aggregate shocks, which is costly. These costs can generate costs of aggregate fluctuations, which exceed those in a frictionless economy.

in the last section is collaborative work of Rocio Madera and myself.

Chapter 2

Occupational Switching and Wage Risk

This chapter is based on Busch (2017).[1]

2.1 Introduction

Many economic decisions hinge on labor income risk faced by individuals: among others, savings behavior and portfolio choice (e.g., Carroll, 1997, or Guvenen, 2007), or fertility decisions. Accordingly, understanding labor income risk is important for a number of macroeconomic phenomena–ranging from the wealth distribution (Aiyagari, 1994), over asset prices (Constantinides and Duffie, 1996), to the welfare costs of idiosyncratic risk (Storesletten et al., 2001b).

The traditional approach to evaluate the extent of labor income risk is to analyze labor income data (prominent examples are Moffitt and Gottschalk, 2002, Guvenen, 2009, or more recently Guvenen et al., 2016). However, income dynamics observed in the data are always the result of an interplay between risk and decisions made by workers, the latter partly in reaction to the former. Starting with the analysis of the labor market histories of young men by Topel and Ward (1992), the literature shows that job-to-job transitions play a key role for wage dynamics realized by workers during their career.

In this chapter, I zoom in on job-to-job transitions and find that a large share of workers

[1]I thank Helge Braun, Fatih Guvenen, Alex Ludwig, and Martin Scheffel for detailed comments on the work in this chapter. Special thanks also go to David Domeij, Michael Krause, Ludo Visschers, and David Wiczer. I thank participants of the 2016 SED meeting in Toulouse, the XXI Workshop on Dynamic Macroeconomics in Vigo, the IZA-CMR PhD workshop, the CMR lunch seminar, the BGSE-CMR Rhineland workshop, the Minnesota Macro Labor workshop, and the University of Edinburgh for helpful comments. I thank the St. Louis FED, the University of Minnesota, and the University of Edinburgh for their hospitality.

switch to different types of jobs: on average, about 40% of workers that change jobs also change occupations (in a classification with 30 occupational groups). While I document this observation for the German labor market using a representative administrative data set from social security records, it appears to be a common feature of labor markets with very different institutional settings (see Carrillo-Tudela and Visschers, 2014, for the US, or Carrillo-Tudela et al., 2016, for the UK). With respect to the wage changes realized upon the job change, staying in the current occupation or moving to another is of large relevance: both high wage gains and severe wage cuts are realized more frequently by job changers who also switch occupations.

Thus, the decision to switch occupations is a major way for workers to affect their wage outcomes: the realized wage dynamics result from an interplay between the underlying risk and the choice to switch occupations or not. The choice of occupational switching enables workers to react to shocks and thereby potentially mitigate negative realizations of shocks–or to realize high wage gains related to a different occupation. In order to disentangle the two, it is not sufficient to look at income data alone. Instead, I analyze the evolution of wages together with job-to-job transitions, explicitly taking into account the occupation at a given job. By its very nature, the switching decision is endogenous. Hence, I build a structural model of occupational choice that allows to dissect the realized wage change into its *shock* and *choice* components. In other words, the model allows me to evaluate the magnitude and distribution of underlying productivity shocks necessary to generate a distribution of realized wage changes in line with the data.

In a calibrated version of the model that is consistent with the documented patterns of wage changes and occupational switching, I find that the variance of productivity changes realized by switchers (stayers) is 69% (96%) of the variance of the underlying shocks. Thus, if one were to equate the *observed* distribution with the *underlying* distribution, one would make an error of 31% (4%) in terms of the dispersion. Considering the distribution of wage changes for switchers and stayers together, the endogenous choice of switching generates about 26% of the variance of realized productivity changes. For this calculation, I compare to the actual dispersion of productivity changes in the model, the dispersion of a counterfactual distribution, where workers are randomly selected to be switchers or stayers–keeping the overall level of occupational switching constant.

The counterfactual scenario differs from the actual distribution on two ends: some workers would decide to switch but are forced to stay; and some workers would decide to stay but are forced to switch. For the forced stayers, switching would imply a better outcome, i.e., either a smaller negative change of productivity, or a larger positive change. Given that the dispersion is larger once workers endogenously choose the occupation, the second channel is quantitatively more important; this channel can be interpreted as career progression. The first channel can be interpreted as an informal insurance character of occupational switching: the switcher still realizes a negative productivity change, but the counterfactual would be worse. Thus, workers can react to bad luck that affects them in their current occupation: think, for example, of a construction worker who after an accident cannot continue to work as a construction worker, but is able to switch to a physically less demanding occupation. Given that the switching decision appears to have large relevance for productivity changes, I use the calibrated model to calculate the utility gain from the possibility to switch: the gain for the average worker corresponds to 0.78% of per-period consumption.[2]

The main data for the calibration of the model comes from a large sample of labor market histories of workers from administrative German social security records, the SIAB. In the social security data, I document the extent of occupational switching of workers in the German labor market and relate it to wage dynamics. Occupational switching refers to labor market transitions that imply a change of occupation. I document how both the occurrence of switches and the distribution of wage changes varies with the rank of a worker in the wage distribution of her origin occupation and with the distance of the switch. I empirically measure the distance between any pair of occupations using task measures in survey data from the Federal Institute for Vocational Education and Training (BiBB). This is interpreted against the background of occupation-specific human capital that is only partly transferrable across occupations.[3]

In terms of empirical patterns, I find that, first, workers switching occupations face a wider distribution of wage changes than those who change jobs within their current occupation. Downside movements of wages are much more common and more severe for workers that transition through unemployment as compared to direct job switchers. Second, conditional on changing jobs, the probability to switch occupations is about 40% on average. The individual wage in the old occupation matters: the probability to switch is the lower, the higher the wage of a worker is relative to all workers in the same occupation before changing jobs. Third, while the declining pattern of the switching probability by rank holds for both job changes through unemployment and direct job-to-job transitions,

[2]In ongoing work, I also analyze the possibility that workers can trade-off short-term wage losses against long-term gains by moving to a steeper wage profile.

[3]The first empirical paper that emphasizes the importance of performed tasks in the context of specific human capital and its partial transferability across occupations is Gathmann and Schoenberg (2010). Using an earlier version of the administrative data analyzed in this chapter and the same data on task measures, they construct a measure of 'task-tenure' and show its significance for explaining wages. While they estimate the average returns to task-tenure in a Mincer-regression, I explicitly analyze heterogeneity of occupational mobility and transferability of human capital across the wage distribution.

switches are more likely after an unemployment period: about 55% of the moves through unemployment involve an occupation-switch, while this is true for 35% of direct job-to-job switches. On top of this, I find that the probability to switch occupations upon re-entering employment increases strictly with the duration of unemployment.

Related Literature

The model builds on the tradition of island economies a la Lucas and Prescott (1974), and is closely related to Carrillo-Tudela and Visschers (2014). As in their model, idiosyncratic productivity shocks are the driver of worker movements across occupations.[4] Different to their model, reallocation is not necessarily through unemployment, and workers draw from two different distributions of productivity shocks (related to staying and switching). The economy is characterized by occupational islands, each of which is populated by a continuum of workers. Workers stochastically accumulate human capital and are exposed to persistent shocks to their idiosyncratic productivity. They can react to shocks by switching to a different occupation. Switching entails a cost for workers, because human capital is only imperfectly transferrable, whereby the degree of transferrability depends on the distance between occupations. The idiosyncratic productivity shock is drawn from different distributions for workers who stay in the old occupation or workers who switch. The interplay between shocks, and the resulting switching decision (and the implied moves along the human capital ladder) allows the model to generate different distributions of realized wage changes for stayers and switchers. In addition, workers experience taste shocks, which represent how much they like the non-pecuniary characteristics of each occupation.[5] Workers face an exogenous separation shock, and unemployed workers face a search friction. When finding a job, workers have all bargaining power such that wages correspond to marginal productivity.

This chapter is closely related to Low et al. (2010), who also argue that realized income dynamics result from an interaction of underlying risk and worker decisions. They focus on the decision of workers to change jobs and differentiate productivity risk from employment risk, and evaluate the welfare consequences of the different risks using a life cycle consumption-savings model, which features a rich set of government insurance policies. Regarding the analysis of wage dynamics, there are two main differences between this chapter and their analysis. First, they do not address the occupational choice of workers; I show this to be of major importance for realized wage outcomes. Second, they

[4]This is one key difference of the model of Carrillo-Tudela and Visschers (2014) and mine to, e.g., Alvarez and Shimer (2011), or Wiczer (2015), where reallocation is driven by occupation-specific shocks.

[5]In an analysis of the effects of occupational switching on outcomes of workers, Longhi and Brynin (2010) document in survey data of the British Household Panel Survey and the German Socioeconomic Panel, that a large share of switchers report an improvement in job satisfaction.

do not explicitly model the job changing decision of workers; instead they estimate a reduced form income process, in which the selection of workers to change jobs is captured by a first-stage probit regression.

By emphasizing the importance of analyzing economic choices for the understanding of labor income risk, this chapter is related to Guvenen and Smith (2014). Using data on labor earnings and consumption, they estimate a consumption-savings model and infer the amount of risk faced by agents and the degree of insurance against this risk. In the sense that I am interested in the extent to which occupational switching–or its twin, occupational attachment–can help us to understand aggregate phenomena, my analysis is in the spirit of Kambourov and Manovskii (2008), who consider a channel through which occupational mobility relates to income inequality, as well as Wiczer (2015), and Carrillo-Tudela and Visschers (2014).[6] Focusing on the reallocation decision of unemployed, Carrillo-Tudela and Visschers (2014) use data from the Survey of Income and Program Participation (SIPP) to analyze the role of occupational switching upon finding employment for aggregate unemployment fluctuations and the distribution of unemployment duration. They develop a search and matching model that accounts for the observed patterns. On the empirical side, they document that the likelihood of switching the occupation upon reentry increases with the unemployment duration. Their framework is closely related to Wiczer (2015), who builds a model in which unemployed workers are attached to their recent occupation due to specific human capital.

Empirically, Wiczer (2015) constructs a distance measure between occupations based on occupational task measures of the O*NET project. In this regard, his analysis is close to this chapter. However, while his focus is on the role of occupational attachment of the unemployed for long-term unemployment, I focus on the transferrability of specific human capital across occupations by rank of workers. This connects this chapter to Groes et al. (2015), who, using Danish administrative data, analyze how the rank of a worker within the occupation-specific wage distribution affects the observed occupational switching behavior. They document that, first, both workers with a relatively low wage and those with a relatively high wage appear to be more likely to leave the occupation compared to workers closer to the mean wage. Second, the farther up (down) a switcher ranks in the wage distribution of her origin occupation, the more likely she switches to an occupation that pays on average higher (lower) wages than the origin distribution. They rationalize these two facts with a model of vertical sorting across occupations based on

[6] In terms of analyzing effects of occupational matching on wages, the chapter is also related to Guvenen et al. (2015) and Lise and Postel-Vinay (2015), who analyze how (multidimensional) match quality affects wage growth. However, these papers explicitly focus on a life cycle perspective.

absolute advantage.[7]

Huckfeldt (2016) relates occupational switching to the dynamics of earnings and, using data from the Panel Study of Income Dynamics (PSID), documents that earnings losses upon losing a job are concentrated among workers who re-enter employment in lower lanked occupations. While he focusses on negative implications of moving down the occupational ladder for the average worker, I relate the whole distribution of wage changes to occupational switching in either direction.

The remainder of this chapter is structured as follows. Section 2.2 describes the data used in the analysis. Section 2.3 analyzes the distribution of wage changes realized by occupational switchers and the empirical relevance of occupational switching. Section 2.4 introduces a model of occupational switching. Section 2.5 discusses the calibration of the model, and analyzes, first, the role of switching for wage changes, and, second, the utility gain from the availability to switch occupations. Section 2.6 concludes.

2.2 Data and Sample Selection

This section provides a description of the data sets used in the empirical analysis, as well as an overview of the sample selection criteria. The main data set is the SIAB, which has been used for the analysis of earnings and wage dynamics in, e.g., Busch et al. (2016), Card et al. (2013), or Gathmann and Schoenberg (2010). The BiBB surveys have been used to characterize occupations in, e.g., Gathmann and Schoenberg (2010), or recently by Becker and Muendler (2015).

The SIAB data

The analysis is based on a sample from social security records provided by the Institute of Employment Research (IAB) of the German federal unemployment agency. The data set covers 2% of all workers who are employed and subject to social security contributions from 1976 to 2010, implying that civil servants and students are not covered. Throughout the analysis, the focus is on males working in West Germany. After applying the usual selection criteria, the sample comprises on average 55,000 individuals per year, with about 430,000 individuals in total. For a detailed description of the data, see vom Berge et al. (2013).[8]

[7] Their model features learning of workers about their own skills. In my model, there is no ex ante heterogeneity of workers (in either a one- or a multi-dimensional skill), and thus learning about oneself does not play role for the analyzed mechanism. A recent overview of papers that model worker learning about skills or talent can be found in Sanders and Taber (2012).

[8] Incomes in the SIAB are top-coded: I implement the same imputation procedure as described in appendix B.1.3.

The BiBB data

Information on the skill and task content of occupations is taken from a set of surveys conducted by the Federal Institute for Vocational Education and Training (BiBB) with wave-specific cooperation partners. The waves are 1979, 1986, 1992, 1999, 2006, and 2012. The cross-sectional surveys each cover a representative sample of about 30,000 respondents and contain information on the tasks performed by workers and on the skills required by their job. Importantly for the present analysis, respondents report their occupations, which allows the aggregation of task and skill measures to the level of occupations. I use data from the first five waves and merge the generated occupation-level information to the SIAB sample. A comprehensive description of the data can be found in Gathmann and Schoenberg (2010).

Sample Selection

While East German employment spells since unification are observed in the data, the analysis focuses on West Germany. East Germany went through a transition period from a planned economy to a market economy and hence the economic forces governing wages, and, of prime importance for this chapter, occupational choices, were very different than those in West Germany. I consider full-time employment spells only and focus on those employment relationships that have some minimum stability, which I define as a minimum duration of two months. I drop observations for ages below 25 or above 54. All reported results are for males.

2.3 Wage Changes and Occupational Switching

2.3.1 The Concept of Occupations in the Data

Definition of Occupations

Occupations are defined by the *KldB88* – the 1988 version of the German employment agency's classification of occupations, which is consistently available in the data. I use the classification at the level of *occupation segments*, which comprises 30 groups of occupations. At this level, potential problems of misclassification can be expected to be small. Examples for the groups are "Painter and similar", "Carpenter, model makers", "Organization-, Administration-, Office- related", or "Physicist, Engineer, Chemist, Mathematician". Table A.1 shows all 30 groups.

Measurement of Tasks and the Distance Between Occupations

At several points in the analysis, I will consider the *distance* of an occupational switch. The distance is measured in the dimension of tasks, building on the concept of an occupation as a combination of tasks (cf. Autor, 2013, or Acemoglu and Autor, 2011). To the extent that human capital is task-specific, as argued, among others, by Gathmann and Schoenberg (2010), the economic implications of switching occupations vary with the *distance* in the task dimension between old and new occupation.[9]

Due to the lack of direct information on tasks performed by the workers observed in the SIAB, the analysis uses external information on task usage at the level of occupations. Task data comes from representative surveys by the BIBB (see section 2.2). I follow Becker and Muendler (2015) and define 15 time-consistent task categories and then calculate the share of workers in each occupation that performs any given task.[10]

Based on this measure, I calculate the distance between any two occupations o and o'. Following the literature (cf. Gathmann and Schoenberg (2010)), my preferred measure of distance is

$$d_{oo'} \equiv 1 - \frac{\sum_{j=1}^{J} (q_{jo} \times q_{jo'})}{\left[\left(\sum_{j=1}^{J} q_{jo}^2\right) \times \left(\sum_{j=1}^{J} q_{jo'}^2\right)\right]^{1/2}}, \tag{2.1}$$

where q_{jo} denotes the share of workers in occupation o who perform task j. The fraction on the right-hand side is the angular separation, which is a measure of proximity that takes only differences in the relative occurence of tasks into account.[11] I calculate the distance measure for all pairs of occupation segments in each cross-section of the BIBB and then merge the distance measure to the SIAB sample of worker histories.[12]

The Ranking of Workers

The ranking of a worker i of age a within the occupation-specific wage distribution in a given month t is based on age adjusted (log) wages, $w_{i,a,t}$. The age adjustment removes

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[9] An alternative to the task based characterization of occupations is to resort to measures of skills required to perform the tasks (e.g., Guvenen et al., 2015). Because I do not analyze the matching of skill requirements to the skills of workers, but rather use the occupation level information to measure the distance between occupations, the two approaches can be expected to yield similar results if similarity of occupations in terms of performed tasks correlates strongly with similarity of skill requirements. Given that some of the task categories used in the analysis are explicitly based on skill requirements, the applied distance measure reflects differences along the lines of applied skills.

[10] I thank Sascha Becker for providing details on the task imputation procedure developed in Becker and Muendler (2015).

[11] Consider an example with two tasks and two occupations, where both occupations are characterized by the same overall mix of tasks. In occupation 1, all workers perform both tasks, while in occupation 2, half of the workers performs task 1 exclusively and the other half performs task 2 exclusively. The distance as measured by (2.1) between the two occupations is zero. The measure is long-established in the literature on R&D spillovers, where research intensity of firms in different technologies is used to characterize the proximity of firms (cf. Jaffe, 1986).

[12] I merge the distance measure from the 1979 BIBB wave to switches in the SIAB which occur between 1980 and 1982, from the 1986 wave to switches in 1983-1988, from the 1992 wave to switches in 1989-1994, from the 1999 wave to switches in 1995-2001, and from the 2006 wave to switches in 2002-2010.

the economy-wide average age profile, however, it does not remove potential heterogeneity of age profiles across occupations. Let $\tilde{w}_{i,a,t}$ be the raw (log) wage. I achieve the age adjustment by subtracting from $\tilde{w}_{i,a,t}$ the (adjusted) coefficient on the relevant age dummy, d_a, from a regression of raw (log) wages on age and cohort dummies, as well as a constant:

$$\tilde{w}_{i,a,t} = \beta_0 + \sum_{j=2}^{A} \tilde{d}_j^{age} \mathbb{1}\left\{a = j\right\} + \sum_{k=2}^{C} \tilde{d}_k^{cohort} \mathbb{1}\left\{c = k\right\}. \tag{2.2}$$

The coefficients on the age dummies are rescaled to the mean wage at the youngest age: $d_1 = \beta_0$ and $d_{a\epsilon[2,A]} = \beta_0 + \tilde{d}_a^{age}$, which then give $w_{i,a,t} = \tilde{w}_{i,a,t} - d_a$. Based on this measure, workers are ranked cross-sectionally relative to other workers in their occupation. The monthly ranking considers all workers who work in a full-time employment spell that lasts for at least three months, and at least two weeks lie in the given month.

2.3.2 *Realized* Wage Changes Upon Switching Occupations

Given the definition of occupations, I turn to the distribution of wage changes realized by occupation switchers and relate them to the wage changes realized by occupation stayers. I classify a worker as occupation stayer (switcher) if he changes the job and the occupation at the new job is the same as (different than) the one at the previous job.[13] Further, I differentiate direct job changes, which I refer to as Employer-to-Employer transitions (E-E), and job changes which go through unemployment (E-U-E). I consider unemployment spells of up to one year, and treat a transition to be a direct job change when the unemployment spell is shorter than one month.

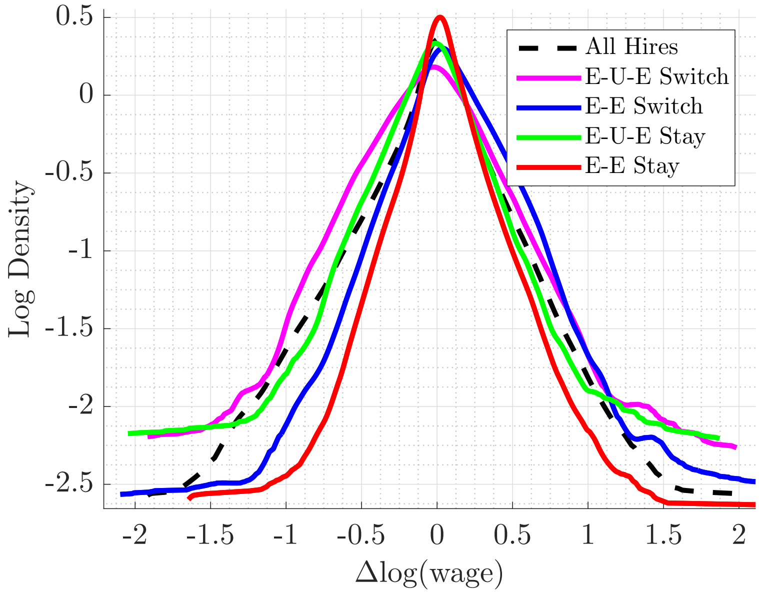
A First Look at the Distribution of Wage Changes

Figure 2.1 shows the smoothed log-density function of wage changes upon changing jobs for four groups: stayers vs. switchers and E-E vs. E-U-E transitions. The individual wage change is calculated as the difference between the logs of the wage at the new job and at the old job. From the four groups, the distribution of wage changes for workers that transition directly and stay within their occupation displays the smallest dispersion. Occupation switchers realize both more wage losses and more wage gains upon changing jobs directly. Overall, the distribution is more skewed to the right, with the right arm of the density shifting farther out than the left arm relative to occupation stayers. This is compatible with voluntary occupation switches that entail career progression.

Turning to the transitions through unemployment, as would be expected, a big share of

[13] In the SIAB data, the establishment of a worker during an employment spell and hence a change of establishment–referred to here as a job change. By focusing on these job changers, I follow the notion of career changes in Carrillo-Tudela et al. (2016).

Figure 2.1: Distribution of Wage Changes



Note: Log-density of wage changes upon changing jobs based on a pooled sample. The non-parametric estimates are smoothed using a locally weighted regression with span 0.05.

the workers reentering the labor market faces a wage loss relative to the pre-unemployment job. Comparing the distribution of wage changes of occupation switchers to the one for stayers that go through unemployment, I find higher losses for switchers. This is compatible with involuntary occupation switching, where workers first search within their old occupation and, after not being successful for a while, decide to search in another occupation. Given the administrative character of the data, which does not provide us with information regarding the actual search strategy of the unemployed, this is something I cannot explore in more detail.

Quantile Regression Analysis

While the preceding analysis of wage changes by means of the log density plots can deliver a good first intuition, it cannot shed light on the role of continuos variables for wage changes, such as the distance of a switch or the rank before changing jobs. I address this by fitting a set of quantile regressions, which are a useful tool to analyze how different parts of the conditional distribution of wage changes differ with a set of observable characteristics (Koenker and Hallock, 2001). Overall, these regressions confirm and quantify the intuitive insights from above.

The regressions take the following form:

$$quan_{\tau}\left(\triangle \log\left(wage\right)\right) = \beta_0\left(\tau\right) + \beta_1\left(\tau\right) Rank + \beta_2\left(\tau\right) Unemp + ...$$
$$Switch \times \left(\beta_3\left(\tau\right) + \beta_4\left(\tau\right) Rank_{i,t} + \beta_5\left(\tau\right) Unemp + \beta_6\left(\tau\right) Distance\right) + \ldots$$
$$\sum_{t=2}^{T} \gamma_t\left(\tau\right) \mathbb{1}\left(year = t\right) + u, \quad (2.3)$$

where $quan_{\tau}\left(\triangle \log\left(wage\right)\right)$ is the τ's quantile of the distribution of (log) wage changes conditional on the explanatory variables:[14] *Unemp* is a dummy variable that takes on value one if the transition is through unemployment and zero otherwise; *Switch* is a dummy variable for occupational switching; *Rank* measures the rank in the last job in vintiles; *Distance* measures the distance between the old and the new occupation; $\mathbb{1}\left(year = t\right)$ represents year dummies; and u is an error term.

The coefficients of the quantile regressions are plotted in Figure 2.2 along with 95% confidence bands.[15] The reported coefficients for the constant are normalized by the average year fixed effect. Consider first the coefficients on the rank in the last job, which are negative for all quantiles: the higher a worker is ranked relative to other workers in the same occupation, the more severe (relatively) are the adverse implications for wage changes of a job change. The point estimates imply that the median worker that changes the job within the same occupation faces a distribution of wage changes with an about 0.07 lower 10^{th} percentile and an about 0.15 lower 90^{th} percentile than the worker from the lowest rank.[16] Workers that go through unemployment realize a distribution of wage changes that is shifted down relative to job changers that do not experience an unemployment spell: the workers at the 10^{th} percentile of wage changes realize an about18 log points bigger wage cut than those at the 10^{th} percentile among the direct job changers. At the 90^{th} percentile, the wage cut is larger by about 3 log points.

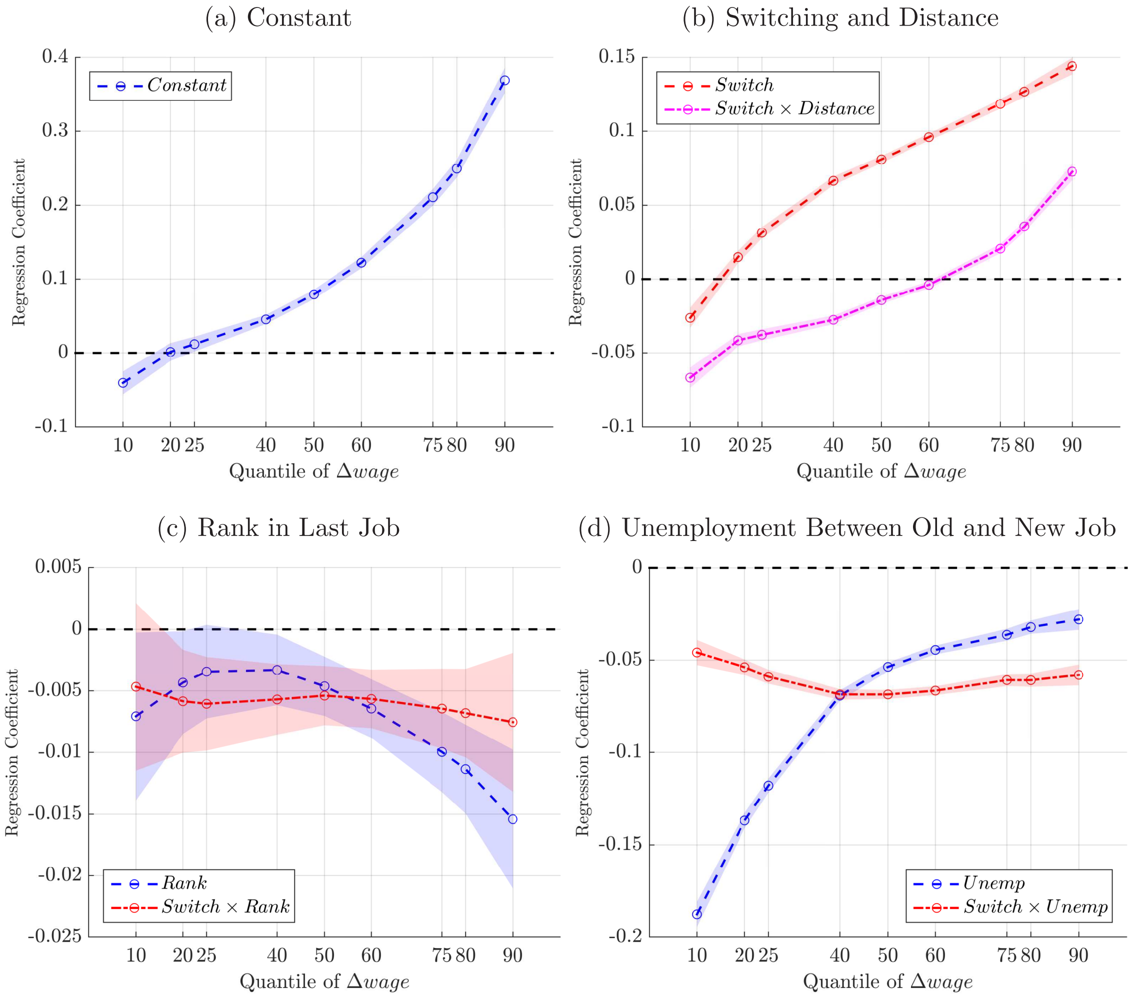
Turning to the occupation switchers, the positive slope of the coefficients on the switch-

[14]It might be helpful to think about the quantile regression models relative to a "standard" linear regression model: coefficients of the quantile regression model for quantile τ predict the τ^{th} quantile of the conditional distribution, while coefficients of the linear regression model predict the conditional mean. Estimation is performed by maximum likelihood, where the objective function is (minus) the sum of weighted absolute deviations from the predicted value, with quantile-specific weights for positive and negative deviations.

[15]Confidence bands are based on the standard deviation of the coefficients from 200 bootstrap repetitions. Bootstrap samples are clustered at the individual level in order to preserve the auto-correlation structure of wages.

[16]The rank is measured in vintiles, so the median worker is in rank 10.

Figure 2.2: Coefficients of Quantile Regressions



Note: Each plot shows the coefficients from quantile regressions for log wage change for several quantiles; the regression includes a constant and year fixed effects as specified in (2.3). Rank can take on values 1-20, and the distance is between 0 and 1. 374,139 observations (sample of job changers).

ing dummy by quantile confirm that the distribution of wage changes is wider than for job changers within the same occupation. Considering the distance of the switch, the coefficients imply the distribution is the wider, the farther the switch. Regarding job changers within the same occupation, the wage gains are lower if the worker ranked higher. Last, relative to a direct job changer, a worker who switches occupations after an unemployment spell faces a penalty for the unemployment period that is more pronounced than the unemployment penalty for the workers that stay in their occupation.[17]

[17]The anlysis shown here focuses on the distribution of instantaneous wage changes. However, the occupational switching decision of workers can be assumed to be based on expectations about future wage implications. In ongoing work, I am evaluating this channel by considering the relationship between switching and medium-run, i.e., 5-year, wage changes. Also, I am analyzing the impact on wage growth

2.3.3 The Amount of Occupational Switching

Given that occupation switchers realize a more dispersed distribution of wage changes upon changing jobs, is it a relevant share of workers that switch occupations? In what follows, I show that occupational switching is indeed an empirically important phenomenon.

The probabilities of switching occupations across quantiles of the occupation-specific wage distribution are shown in Figure 2.3. The population used to estimate the monthly switching probabilities comprises all workers that, after having worked in full-time employment previously, start a new employment spell in month t. I estimate the probability of switching occupation o for a worker i ranked in rank r, conditional on starting a new job, non-parametrically as

$$Pr\left\{Switch^i | job_{i,new} \neq job_{i,old} \wedge rank_{i,old} = r\right\} = \frac{\sum_j \mathbb{1}\left\{o_{i,new} \neq o_{i,old} \wedge rank_{i,old} = r\right\}}{\sum_j \mathbb{1}\left\{job_{i,new} \neq job_{i,old} \wedge rank_{i,old} = r\right\}}. \quad (2.4)$$

Figure 2.3a shows that across wage ranks, the probability of leaving the occupation upon changing jobs is high. Among the workers coming from the bottom five percent of the wage distribution in their old occupation, the share of workers leaving their job for another occupation is highest at about 55%. Up to the 80^{th} percentile, the switching probability displays a declining pattern, which then flattens out at about 37%. [18]

Differentiating direct job changes from those through unemployment, Figure 2.3a reveals that, across ranks, it is more likely for workers to switch occupations when they experience a period of unemployment: on average, about 55% of the job changers that went through unemployment switch occupations, with a decreasing pattern from about 64% for workers coming from the bottom five percent to around 53% for the highly ranked workers. Out of all workers who do not go through unemployment, on average, about 35% switch occupations. Again, the pattern across ranks is declining with about 46% of workers from the bottom and 30% from the higher ranks switching.

In Figure 2.3b, I consider the role of unemployment duration, and find that the share of workers switching occupations increases with the duration of unemployment. For workers from the lower half of the occupation-specific wage distribution before entering unemployment, it stays constant at around 55% for the first five months, after which it increases in a

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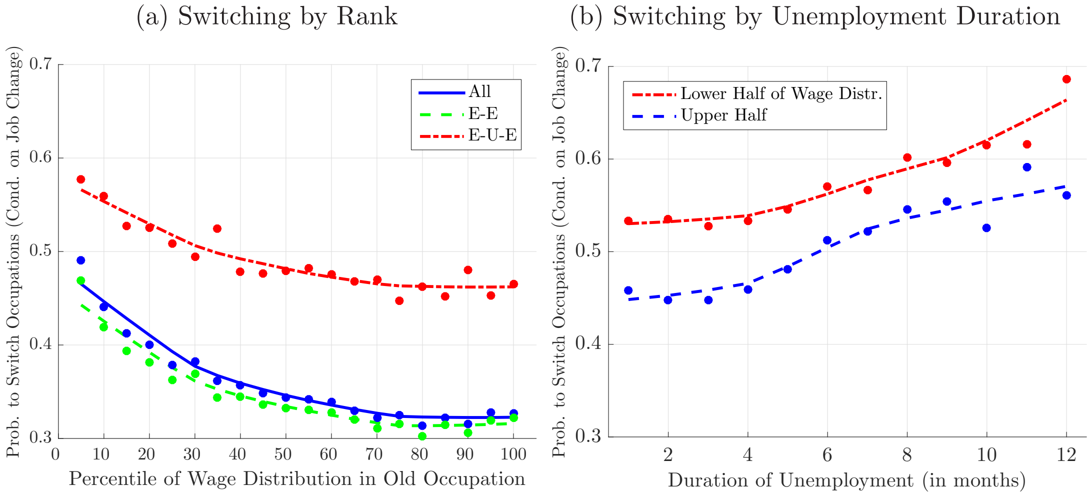
after the switch. Preliminary results do not suggest that workers do not trade-off short-term losses against a steeper wage profile.

[18] Note that Groes et al. (2015) analyze a similar switching pattern for Denmark. However, they analyze annual earnings data (while I look at monthly wage data) and find a pronounced U-shape of the switching probability by rank.

Figure 2.3: Probability of Switching Occupations



Note: Non-parametric probabilities. Smoothed using locally weighted regressions with a 1st degree polynomial. Only workers with unemployment duration up to one year are considered.

roughly linear fashion up to just below 70% for workers leaving unemployment in the 12^{th} month. The switiching probability for workers from the upper half of the occupational wage distribution displays a similar pattern, with a constant probability of about 45% in the first four months, increasing to about 55%.[19]

2.4 A Model of Occupational Switching

2.4.1 Overview of the Model Economy

In this section, I build a stationary model of the labor market in which workers discretely choose their sector of employment. The model allows us to shed light on the relative roles of occupational choices and of productivity shocks for realized income changes. More precisely, using the model, I can calibrate aspects of the distribution of shocks consistent with observed wage changes. This allows me to analyze occupational switching as an insurance device against income risk that is related to the occupation of current employment.

Time is discrete and the labor market is characterized by a finite number of sectors, or "islands", which resemble occupations. This island structure of the labor market is similar to Pilossoph (2014) and Carrillo-Tudela and Visschers (2014), which are versions of the Lucas and Prescott (1974) framework. Each island is populated by a continuum of firms, which use effective labor as an input in a linear production technology. Unemployed

[19] Controlling for the role of age for switching, I estimate a linear probability model of switching a switching dummy on a full set of dummies for age, rank, transition type (unemployment dummy), and year fixed effects. The profile is decreasing in age.

workers searching for a job face a search friction on each island, which implies that a worker-job match generates quasi-rents. I assume that workers have all the bargaining power and thus are paid according to their marginal product. Focussing on a partial equilibrium analysis, I keep the firm side as simple as possible, and do not endogenize the job finding probability. Each pair of occupations is characterized by an exogenous distance, which reflects the concept of an occupation as a certain combination of tasks.

While employed in an occupation, workers move up a ladder of occupation specific human capital at a stochastic rate. On top of this experience profile, workers receive persistent stochastic shocks to idiosyncratic productivity, that are orthogonal to human capital. I refer to the combination of occupation specifc human capital and the persistent shocks as idiosyncratic productivity. Workers randomly select an alternative occupation, costlessly search on-the-job for alternative jobs, and receive a job offer with some probability. Given an offer, workers decide whether to accept or stay with their current job (in their current occupation). Human capital is perfectly transferrable across jobs within an occupation island, but imperfectly transferrable across islands.

Workers lose their job with an exogenously given probability and become unemployed. Unemployed workers decide whether to search for employment in their old occupation or to switch to another occupation and search for employment there. As for employed workers, the job finding probability is exogenously given and the same across all islands. While unemployed, the stochastic component of idiosyncratic productivity does not change, and each period, an unemployed worker steps down the ladder of occupation specifc human capital with some probability.

The decision of both employed and unemployed workers whether to stay on their current island or move to the (randomly selected) alternative island depends on both wage-related and non-pecuniary aspects. The wage-related aspects are that, when starting a new job, both components of idiosyncratic productivity (and hence, wages) are affected by the choice of the worker. First, when switching to another occupation, the worker enters it at a lower human capital level – the more distant the occupations are, the more steps on the ladder the worker jumps down. Second, the stochastic skill shock is drawn from a different distribution for occupation stayers and occupation movers.

The non-pecuniary aspect affecting the decision of where to search for a job is a worker's *taste* for the different occupations: I assume that, each period, each worker draws a vector of tastes for all islands from distributions that are independent and identical over workers, islands, and over time.[20]

[20] Recent examples of models that use taste shocks in the context of occupational switching are Wiczer (2015) and Pilossoph (2014). The taste shocks over occupations are a shortcut to achieving worker

My model is a model of gross flows across occupations and in this respect similar to Carrillo-Tudela and Visschers (2014). This implies that the occupational employment share is constant over time. The reason for this choice is that I am interested in the reallocation across occupations in the individual decision problem and its relation to the wage process. In order to analyze this decision, I do not need any correlation of shocks across workers.

2.4.2 The Environment

There is a discrete number of occupational islands. The set of these islands is denoted by O, and each is populated by firms offering one job each, operating a production technology that is linear in idiosyncratic worker productivity. Each pair (o_i, o_j) of occupations is characterized by a distance $d(o_i, o_j)$. A period is divided into three stages: a pre-production stage, a production stage, and a post-production stage.

Stochastic Productivity Stochastic idiosyncratic productivity is denoted by $x_{i,t}$ and follows an $AR(1)$ in logs. A worker enters the pre-production stage with productivity $x_{i,t}$ and draws two shocks, $\boldsymbol{\eta}_{i,t} = \left\{\eta_{i,t}^{stay}, \eta_{i,t}^{move}\right\}$, where $\eta_{i,t}^{stay} \sim F_{\eta,t}^{stay}$ and $\eta_{i,t}^{move} \sim F_{\eta,t}^{move}$. If the worker works during the production stage, the stochastic productivity component is given by

$$\begin{aligned} \log(x_{i,t+1}) = g^e\left(x_{i,t}, o_{i,t}, o_{i,t+1}; \boldsymbol{\eta}_{i,t}\right) \equiv \\ \rho \log(x_{i,t}) + \mathbb{1}\left\{o_{i,t+1} = o_{i,t}\right\} \eta_{i,t}^{stay} + \mathbb{1}\left\{o_{i,t+1} \neq o_{i,t}\right\} \eta_{i,t}^{move}, \end{aligned} \tag{2.5}$$

where $\mathbb{1}\{*\}$ is an indicator function taking the value 1 if $*$ is true and the value 0 otherwise: only one of the two shocks is relevant for productivity. If the worker is unemployed during the production stage, $x_{i,t}$ does not change.

Human Capital Human capital of a worker i evolves stochastically and can take on H discrete values $h_{i,t} \in \{h_1, ..., h_H\}$, where $h_1 < h_2 < ... < h_H$. A worker who enters period t in the pre-production stage with human capital level $h_{i,t} = h_j$ in occupation $o_{i,t}$ and who ends up working in occupation $o_{i,t+1}$, has human capital level $\tilde{h}_{i,t+1}$ during the production stage, where

$$\tilde{h}_{i,t+1} = h_{j-k}, \text{ with } k = f\left(d\left(o_{i,t}, o_{i,t+1}\right)\right), \tag{2.6}$$

where $f\left(d\left(o_{i,t}, o_{i,t+1}\right)\right)$ pins down how many steps of the human capital ladder the worker moves down depending on the distance, where $f(0) = 1$ and $f(1) = \kappa$, where $\kappa <$

heterogeneity beyond skill heterogeneity in the cross-section.

$H-1$ denotes the number of steps a worker moves when switching to the most different occupation. This captures that the degree of transferrability of skills across occupations depends *systematically* on the distance between occupations. If a worker is employed in the production stage with human capital level $\tilde{h}_{i,t+1} = h_k$, then, during the post-production stage,

$$h_{i,t+1} = \begin{cases} h_{k+1} & \text{with probability } \psi_k^{hup} \\ h_k & \text{with probability } 1 - \psi_k^{hup} \end{cases}. \tag{2.7}$$

The probability of stepping up depends on the current position on the ladder, and $\psi_k^{hup} > \psi_{k+1}^{hup} \forall k$, i.e., the probability of stepping up the ladder decreases with the current position. This notion of steps that become steeper allows the model to generate a profile of the switching probability that is decreasing in human capital. Once at the highest level, h_H, a worker stays there with probability 1–unless he switches occupations or becomes unemployed.

If a worker is unemployed during the production stage and the human capital level is $\tilde{h}_{i,t+1} = h_k$, then, during the post-production stage, the worker moves down one step with probability ψ^{hdown}:

$$h_{i,t+1} = \begin{cases} h_{k-1} & \text{with probability } \psi^{hdown} \\ h_k & \text{with probability } 1 - \psi^{hdown} \end{cases}. \tag{2.8}$$

Separation and Job-Finding In the pre-production stage, a worker is separated exogenously with probability $1-\phi$. A separated worker is unemployed during the production stage and enters the next period as unemployed. Both employed and unemployed workers receive job offers, with probabilities ψ^e and ψ^u, respectively. There is no congestion in the labor market, and workers have all bargaining power, resulting in marginal product wages.

Life Span I focus on the stationary equilibrium of the economy and in order to ensure a realisitc equilibrium distribution over wages and human capital, agents leave the economy with a constant probability of death, $1 - \pi < 1$. For each worker who dies, a new worker enters the economy, generating a perpetual youth structure a la Blanchard (1985) and Yaari (1965), such that the population is of constant size. Newborns enter the economy as unemployed at the lowest human capital level, with average stochastic productivity, and randomly attached to one of the occupations.

2.4.3 The Decision Problem of Workers

Employed Workers Workers maximize their expected discounted lifetime utility. When employed at the beginning of the period t, a worker i is characterized by his occupation $o_{i,t}$, his level of human capital $h_{i,t}$, and his stochastic idiosyncratic productivity $x_{i,t}$. Also, workers enter the period with a vector $\mathbb{O}_{i,t}$ of tastes for occupations. If not separated, the worker randomly chooses in which alternative occupation to search for a job. Then the worker draws two idiosyncratic productivity shocks, $\boldsymbol{\eta}_{i,t} = \left\{\eta_{i,t}^{stay}, \eta_{i,t}^{move}\right\}$ from distributions $F_{\eta,t}^{stay}$ and $F_{\eta,t}^{move}$. Search is costless, and with probability ψ^e an offer arrives and the worker chooses whether to stay in the current occupation or move to the other. The human capital level at the production stage depends on this choice according to (2.6). If no offer is received, the worker stays with his current job (and occupation). The worker receives wages according to the total productivity and consumes all income, i.e., $c_{i,t+1} = x_{i,t+1} \times \tilde{h}_{i,t+1}$. I assume a linear utility function and hence per-period utility at the production stage is given by

$$\widetilde{u}^{empl}\left(x_{i,t+1}, o_{i,t+1}, \tilde{h}_{i,t+1}\right) = x_{i,t+1} \times \tilde{h}_{i,t+1}. \tag{2.9}$$

The recursive problem is given by

$$\begin{aligned} V^{empl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) = \phi \times \Bigg(&\psi^e \times V^{offer}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) + \ldots \\ &(1-\psi^e) \times V^{stay}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right)\Bigg) + \ldots \\ &(1-\phi) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E\left[V^{unempl}\left(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right)\right]\right) \end{aligned} \tag{2.10}$$

$$\begin{aligned} &s.t. \\ x_{i,t+1} &= x_{i,t} \\ h_{i,t+1} &\text{ acc. to } (2.8) \end{aligned}$$

where I express the value function with the adjusted discount factor $\widetilde{\beta} = \beta\pi$, with β denoting the pure discount factor and π the probability of survival. If the worker loses the job in the pre-production stage, he stays unemployed in period t and enters the next period unemployed with $o_{i,t}$ indicating the occupation of his last employment, while idiosyncratic productivity remains constant. If the worker does not lose his job, and receives no alternative job offer, he stays with the current job; when receiving a job offer, he can choose whether to stay with the current job or to move to another occupation.

The sub value functions are given by $V^{stay}(\bullet)$ and $V^{offer}(\bullet)$ as follows.

$$V^{stay}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) = \widetilde{u}^{empl}\left(x_{i,t+1}, o_{i,t}, \tilde{h}_{i,t+1}\right) + \dots$$
$$\widetilde{\beta} E\left[V^{empl}(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}) + \mathbb{O}_{i,t+1}(o_{i,t})\right] \quad (2.11)$$

$$\begin{array}{lcl} s.t. & & \\ x_{i,t+1} & = & g^{e}\left(x_{i,t}, o_{i,t}, o_{i,t}; \boldsymbol{\eta}_{i,t}\right) \\ \tilde{h}_{i,t+1} & = & h_{i,t} \\ h_{i,t+1} & \text{acc. to} & (2.7) \end{array}$$

and

$$V^{offer}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) =$$
$$\widetilde{\beta} \times \sum_{j \neq o_{i,t}} \pi_j \times \max\left(\tilde{v}(j|\bullet) + E_{\mathbb{O}}\mathbb{O}_{i,t+1}(j), \tilde{v}(o_{i,t}|\bullet) + E_{\mathbb{O}}\mathbb{O}_{i,t+1}(o_{i,t})\right) \quad (2.12)$$

where π_j is the probability that the worker randomly chooses occupation j in the pre-production stage and $\tilde{v}(j|\bullet)$ is given by:[21]

$$\tilde{v}(j|\bullet) = \widetilde{v}(j|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) \equiv$$
$$\frac{1}{\widetilde{\beta}}\widetilde{u}^{empl}\left(x_{i,t+1}, j, \tilde{h}_{i,t+1}\right) + E_{\boldsymbol{\eta}, \psi^{hup}} V^{empl}(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, j).$$

$$\begin{array}{lcl} s.t. & & \\ x_{i,t+1} & = & g^{e}\left(x_{i,t}, o_{i,t}, o_{i,t+1}; \boldsymbol{\eta}_{i,t}\right) \\ \tilde{h}_{i,t+1} & \text{acc. to} & (2.6) \\ h_{i,t+1} & \text{acc. to} & (2.7). \end{array}$$

Unemployed Workers A worker entering the period unemployed is characterized by a state vector collecting his last occupation, $o_{i,t}$, his level of human capital, $h_{i,t}$, his stochastic idiosyncratic productivity, $x_{i,t}$, and his preferences over occupations, $\mathbb{O}_{i,t}$. He randomly

[21] I make use here of the independence of taste shocks and productivity (and human capital) shocks.

chooses one alternative occupation $o_{i,t+1}$ in which to costlessly search for a job, while also searching in the old occupation. The unemployed worker then draws two idiosyncratic productivity shocks, $\boldsymbol{\eta}_{i,t} = \left\{\eta_{i,t}^{stay}, \eta_{i,t}^{move}\right\}$ from the same distributions $F_{\eta,t}^{stay}$ and $F_{\eta,t}^{move}$ as employed workers. With probability ψ^u the worker receives a job offer and when staying unemployed at the production stage, the worker receives $\widetilde{u}^{unempl}$. The recursive problem is given by

$$V^{unempl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) = \psi^u \times V^{offer}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) + \dots$$
$$(1-\psi^u) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E V^{unempl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right)\right) \quad (2.13)$$

$$s.t.$$
$$h_{i,t+1} \quad \text{acc. to} \quad (2.8)$$

The Conditional Choice Probabilities

Note that, conditional on receiving an offer, the choice problem of employed and unemployed workers is the same. The introduction of the taste shocks implies that the value function is smooth in the state space $(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$, and that from a group of workers who are at the same position in the state space, every occupation is chosen by some members of the group, because they differ in their tastes. The policy function is thus a set of choice probabilities for each occupation.

I assume $F_{\mathbb{O}}$ to be a Gumbel distribution, which allows me to exploit results from discrete choice theory, as also done recently in, e.g., Pilossoph (2014) or Iskhakov et al. (2015):[22] they yield analytical expressions for the conditional choice probabilities, which for occupation $o_{i,t+1}$ is given by

$$P\left(o_{i,t+1} = j | x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}, (\psi^e = 1 \vee \psi^u = 1)\right) =$$
$$\pi_j \times \frac{1}{1 + \exp\left(\frac{\widetilde{v}(o_{i,t}|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) - \widetilde{v}(j|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})}{\sigma_{\mathbb{O}}}\right)}, \quad (2.14)$$

[22] Iskhakov et al. (2015) provide a detailed discussion of taste shocks as a smoothing device in the solution of discrete choice problems. I denote the scale parameter by $\sigma_{\mathbb{O}}$ and normalize the location parameter as $-\sigma_{\mathbb{O}}\gamma$, where γ is Euler's constant. The normalization is such that the (unconditional) expected value of each taste shock is zero.

where π_j is the exogenous sampling probability of occupation j.

2.5 Calibrated Model

In this section, I analyze a calibrated version of the model. The calibration has two goals. First, it allows me to quantify the relative role of different components of wage changes, i.e., human capital changes and changes of the stochastic productivity. For direct job changers that stay in their occupation, productivity shocks account for about 66% of wage changes, for occupation switchers this number is 49%. Ignoring selection of workers into switching and staying, one would underestimate the variance of productivity shocks for occupation movers by 31% and for stayers by 4%. Second, given that workers choose to switch occupations in response to underlying productivity shocks, I calculate the option value that workers assign to the availability of the switching channel. To this end, I ask workers in a counterfactual world without the option of switching, before the realization of productivity shocks, how much they gain in expectation from the option. As a share of per-period consumption, the answer to the question is 0.78.

The calibration successfully matches the patterns of wage changes for direct job changers (targeted), however, it implies too bad outcomes for job changers through unemployment (non-targeted).

2.5.1 Parameterization and Calibration of the Model

Model Elements Calibrated Exogenously

In the calibrated version of the model, I choose a period to be one month and set the number of (horizontally differentiated) occupations to six. Given symmetry in terms of productivity, having six occupations allows me to define the distance $d_{oo'}$ from one occupation o to any other occupation o' as either 1/3 ("close"), 2/3 ("medium"), or 1 ("far").[23]

Table 2.1 lists the exogenous parameters that are set outside the model. I choose the survival probability π such that the expected duration of a career is 40 years. The monthly probabilities to lose a job when employed and to find a job when unemployed, respectively, are set in line with the average transition rates as documented by Jung and Kuhn (2013). Taking the probablity of death into account, I choose the monthly discount factor to comply with a 4% annual interest rate. Finally, I set the per-period utility of unemployment, $\tilde{u}^{unempl}$, to 80% of the lowest per-period utility level received by an

[23] Visualize the occupations to be distributed equidistantly on a circle. The shortest way to get to another occupation along the circle gives the distance, which I normalize such that the maximum distance is 1.

Table 2.1: Pre-Calibrated Parameters

Parameter	Description	Value	Informed by
π	Probability to survive to next period	.9979	Implied expected duration of career: 40 years (25-64)
ψ^e	Monthly probability of job offer when employed	.01	Average monthly E-E, E-U, and U-E transition rates Jung and Kuhn (2013)
$(1-\phi)$	Monthly probability to loose job	.0005	
ψ^u	Monthly probability of job offer when unemployed	.0062	
β	Monthly discounting factor	.9988	4% annual interest rate

Note: Table shows parameters calibrated exogenously. E and U denote Employment and Unemployment, respectively. β takes the survival probability into account.

employed worker.

Identification of the Remaining Model Elements

Productivity Shocks A key element of the model is its take on the nature of idiosyncratic shocks. In the data, I can only observe the distributions of realized wage changes for workers that endogenously decide either to stay in their occupation or to switch to a different one. The model's key identifying assumption for the underlying shock distributions is that workers make a utility-maximizing choice.

The mechanism can be understood directly in a stripped-down version of the decision problem. Disregarding the human capiral element of the model, just consider the two shocks, η^{stay} and η^{move}, and assume that these directly translate into wage changes depending on the choice of the worker to stay or to move. Given any distributions $F^{stay}_{\eta,t}$ and $F^{move}_{\eta,t}$, the utility maximization of the workers implies that η^{stay} is observed as a wage change whenever the draws are such that $\eta^{stay} > \eta^{move}$ and vice versa. Thus, the probability to observe realization n of the move shock, $\eta^{move} = n$, is a combination of the probabilities that $\eta^{move} = n$ is actually drawn from $F^{move}_{\eta,t}$ and that the realization of the stay-shock is worse, i.e., $\eta^{stay} \leq n$. In other words, the share of realization n in the distribution of wage changes realized by occupation switchers is informative about the lower tail of the distribution of stay-shocks, and vice versa. $F^{stay}_{\eta,t}$ and $F^{move}_{\eta,t}$ are assumed to be Normal distributions, with means and standard deviations denoted by μ^{stay}_{η}, σ^{stay}_{η}, μ^{move}_{η} and σ^{move}_{η}.

Human Capital Ladder In terms of the human capital ladder, the following elements are not yet fixed: the number of steps, H, the step size of the ladder, Δh, the probabilities to step up, ψ_k^{hup}, or down, ψ^{hdown}, and the number of steps down depending on the distance of an occupation switch, $f(d(\cdot))$.

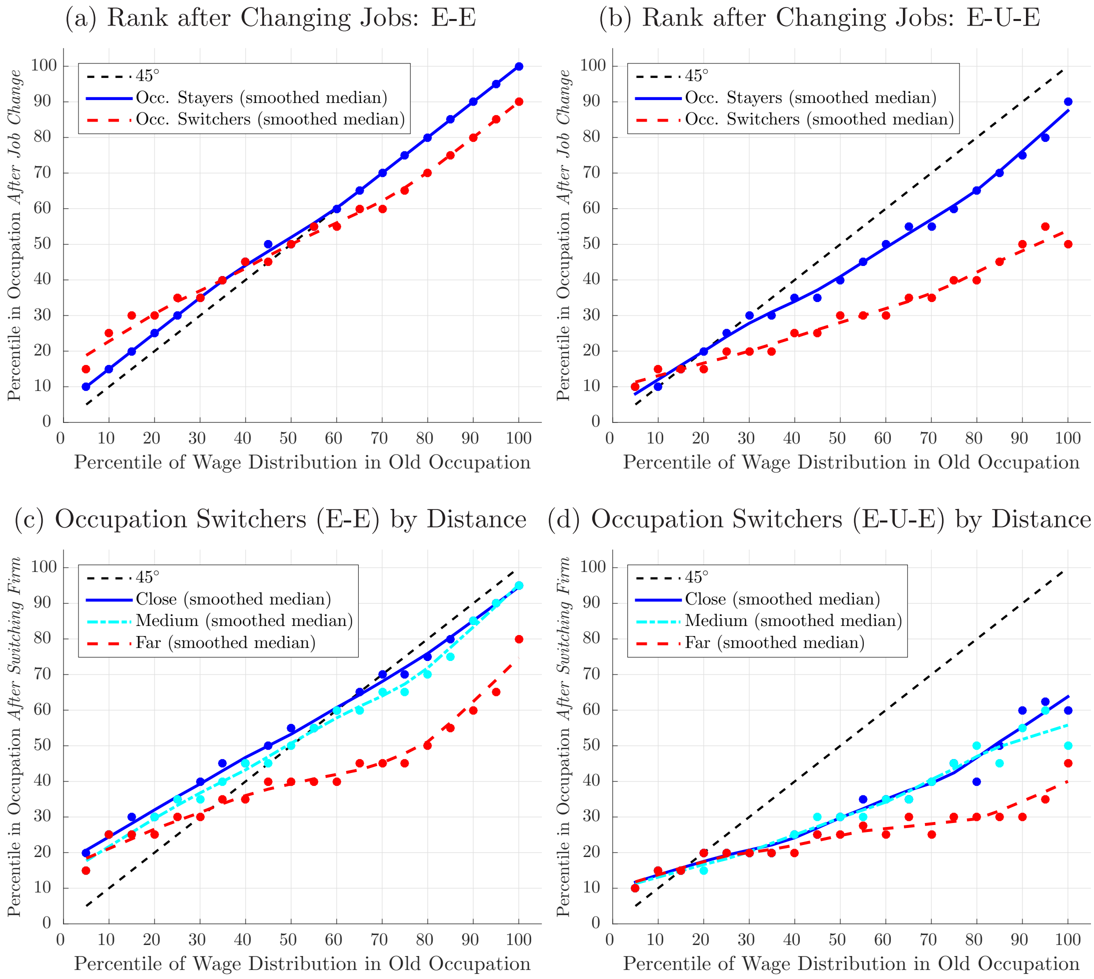
I set the number of steps on the human capital ladder to $H = 11$. Consider the implications of an occupational switch. According to Equation (2.6), a worker moves down the ladder when switching occupations, which implies a wage cut. Above, I defined the distance between occupations to be 1/3, 2/3, and 1. I set the implied number of steps down on the human capital ladder to be 1, 2, and 3, respectively. The empirical motivation for workers stepping down the human capital ladder when switching is as follows. Consider the rank of a worker in the occupation-specific wage distributions before and after changing jobs. Figures 2.4a and 2.4b show that, for both E-E and E-U-E transitions, a worker from higher wage ranks tends to rank relatively lower in the occupational wage distribution when switching occupations. In addition, Figures 2.4c and 2.4d show that, among the occupation switchers, a worker tends to rank relatively lower in the new occupation when the switch covers a greater distance. This is especially true for transitions through unemployment. The three categories of switches ("close", "medium", and "far") are based on grouping workers by distance into three year-specific groups, implying that each group is of equal size.

I calibrate the probability to step up the ladder, ψ_k^{hup}, as a piecewise linear function of the current state k. In the calibration procedure, I set the probability for $k = 1$, $k = 6$, and $k = 10$, and linearly interpolate between these nodes. Why does the probability to step up depend on where you are on the ladder? Other things equal, a higher human capital level implies a higher wage. Now assume that $\psi_k^{hup} = \psi^{hup} \forall k$. The higher a worker is on the ladder, the less relevant is the temporary wage cut from stepping down the ladder: workers with higher wages are willing to accept the wage cut and switch occupations more frequently. To see this, consider the inverse of the probability to choose a given occupation j in Equation (2.14):

$$P\left(o_{i,t+1} = j|\bullet\right)^{-1} = \left(1 + \exp\left(\frac{\widetilde{v}\left(o_{i,t}|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) - \widetilde{v}\left(j|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right)}{\sigma_{\mathbb{O}}}\right)\right) \times \frac{1}{\pi_j}$$

The expected value of occupation j relative to the alternative of staying in the current occupation $o_{i,t}$, weighted by the scale of the taste shocks, is relevant for the choice. Consider the situation with two occupations. Now consider a worker i, currently in occupation 1 with human capital level h_k. At the production stage, the human capital level of that worker is $\tilde{h}_i = h_k$ when choosing to stay in occupation 1, and $\tilde{h}_i = h_{k-1}$ when choosing

Figure 2.4: Relative Position of Job Changers



Note: The scatters show the position of the median worker from the respective group, the lines are smoothed using a locally weighted regression with span 0.5.

to switch to occupation 2. As the worker gets closer to the top of the ladder, keeping the level of the stochastic component and the productivity shocks constant, $\widetilde{v}(1|\bullet) - \widetilde{v}(2|\bullet)$ decreases with the level of human capital h_k (the step down is compensated quicker, because the end of the ladder is reached earlier when choosing to stay). Thus, for the same stochastic productivity levels and shocks, the probability to stay in occupation 1 decreases with human capital if the probability to step up the ladder is constant.

However, the empirical analysis in Section 2.3.3 showed that higher ranked workers are less likely to switch. In order to allow the model to generate this, I let the probability to step up vary with the step on the ladder. If the ladder becomes *steeper* as one walks up (the probabiltiy of stepping up decreases), then this has a positive effect on $\widetilde{v}(1|\bullet) - \widetilde{v}(2|\bullet)$ as a function of the level of human capital. The probabilities to step up are hence identified by the probability of switching as a function of the rank.[24] Unemployed workers move down the human capital ladder one step each period with probability ψ^{hdown}. I documented above that the probability of switching occuaptions increases with the duration of unemployment. This is what identifies this parameter.

The step size of the ladder, Δh, is identified by the right tail of the distribution of wage changes realized by job changers within an occupation. Consider equation (2.7): when staying in the occupation, a share of workers moves up the ladder one step, thus experiencing an increase of human capital by Δh. Similarly, the lower part of the distribution of wage changes realized by occupation switchers is informative for Δh: upon switching occupations, a worker moves down the ladder by at least Δh. The other tails of the respective distributions are governed by the mean parameters of the productivity shocks.

Taste Shocks The scaling factor of the taste shocks, $\sigma_{\mathbb{O}}$, affects the probability of workers to switch occupations. A higher $\sigma_{\mathbb{O}}$ implies that differences of the expected value of being in either occupation are less relevant; in the present model, workers are more willing to accept the human capital loss that comes with switching and switch more frequently. Along these lines, Wiczer (2015) and Pilossoph (2014) argue that the switching rate pins down the scale of the taste shocks. In my model, the switching rates are driven by productivity shocks and taste shocks. The productivity shocks are pinned down by moments of wage changes, and hence there is scope for the taste shocks.

Less obvious, the scaling factor also affects the elasticity of the switching probability with respect to changes of the relative payoffs of staying and switching. To see this, consider again the probability to choose occupation j in Equation (2.14). As discussed above, the probability of switching occupations varies with the level of human capital. If the taste shocks are more dispersed, then a (marginal) change of the relative value of j matters less for the choice (because the difference of expected payoffs is scaled with the inverse of $\sigma_{\mathbb{O}}$). Thus, the pattern of switching by rank is also informative for the scaling of taste shocks.

Wage Changes and Switching Probability

Table 2.2 summarizes the targeted moments and their counterparts in the calibrated model. I calculate the model-implied moments in the stationary distribution of the model

[24]Note that, in the model, the rank of a worker within the occupation-specific wage distribution is not the same as his human capital level: wages are a combination of human capital and the stochastic idiosyncratic component. Given that the ladder gets steeper when walking up, there is a selection process of workers with lower levels of stochastic productivity: workers with higher levels of human capital are willing to accept worse stochastic productivity shocks, because they weigh this against a loss of human capital upon switching from which they (in expectation) recover less quickly.

Table 2.2: Moments–Data vs. Calibrated Model

Moment	Data		Model		Informs
Distribution of (log) wage changes of E-E transitions					
	stayers	switchers	stayers	switchers	
10^{th} percentile	-.11	-.19	-.10	-.23	Productivity shocks; step size of human capital ladder
50^{th} percentile	.02	.04	.03	.05	
90^{th} percentile	.22	.34	.17	.26	
Probability to switch					
Avg. (E-E)	.30		.22		Scaling of taste shocks
By rank (E-E)	(.43, .27, .24)		(.25, .22, .26)		Prob. to step up human capital ladder
increase over 1 year of unemp.	.29		.22		Prob. to step down during unemployment

Note: The table shows data moments that are targeted in the calibration and model counterparts with the calibrated parameters.

economy.[25] As empirical counterpart for these moments, I choose long-run averages. Specifically, for the percentiles of wage changes, I use the fitted percentiles from a set of quantile regressions, similar to the ones outlined in Equation (2.3) in Section 2.3.2. I do not use rank and distance of switch as control variables here, because I target the *average percentiles* of direct job changers for the current calibration. Given the estimates, I add the average of the year-dummy coefficients to the constant, and calculate the fitted percentiles of wage changes for switchers and stayers, respectively.

For the switching probability on average and by rank, I use the predicted probabilities from a linear probability model. The linear probability model regresses a switching dummy on a constant, a set of dummies for the rank, a dummy for the type of switch (1 if E-U-E, 0 if E-E), the unemployment duration (interacted with the unemployment dummy), a full set of year dummies, and dummies for age group; I choose three age groups: 25–34, 35–44, and 45–54. Given that the model does not feature an age dimension[26], I use the predicted switching profile for the second age group as target. In order to generate long-run average

[25] A.3 describes the model solution and the calculation of moments in the stationary distribution.

[26] The model does have a perpetual youth structure, but the probability of death is the same for every worker. Therefore, the model does not generate an horizon effect, in the sense that younger workers would switch more often because they can profit from an investment element of the switching decision longer than older workers. A channel like this can be introduced in the model by having two age groups living at the same time: a young worker then ages with an exogenous probability, and an old worker dies with an exogenous probability.

Table 2.3: Calibrated Parameters

Parameter	Value	Parameter	Value
μ_η^{stay}	-.0075	ψ^{hdown}	24.23%
μ_η^{move}	.0237	ψ_{lo}^{hup}	22.57%
σ_η^{stay}	.0934	ψ_{med}^{hup}	9.97%
σ_η^{move}	.1829	ψ_{high}^{hup}	0.52%
Δh	.7795	$\sigma_{\mathbb{O}}$	.2710

Note: The table shows parameters calibrated using the model.

switching probabilites, I add the average of the year-dummy coefficients. The last target is the average increase of the switching probability over one year of unemployment. For this, I use the predicted average switching profile from a linear probability model of switching on a constant, year dummies, and the unemployment duration (interacted with the unemployment dummy).

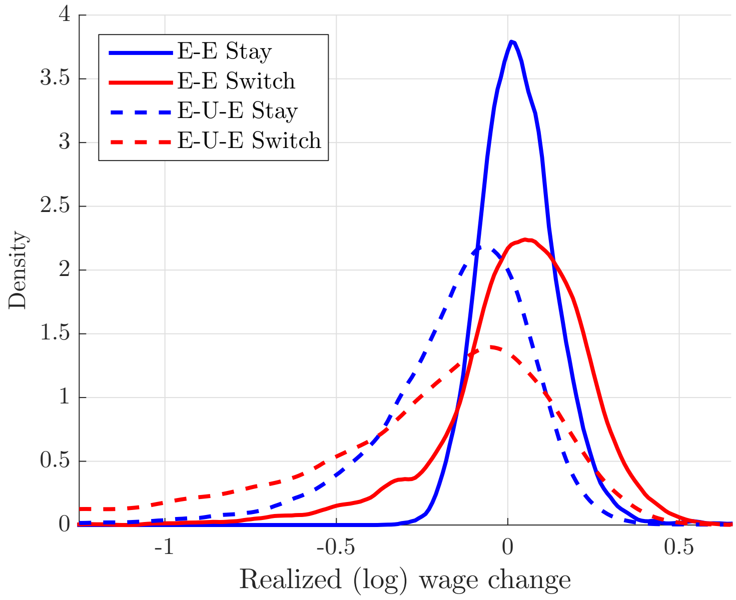
Table 2.3 lists the calibrated parameters. The calibrated model does a good job in matching the pattern of the targeted percentiles of wage changes – the key focus of the analysis. Specifically, the median for switchers and stayers, and the 90^{th} percentile for switchers are fit well (1 log point difference). This is also true for the 10^{th} percentile of wage changes for stayers. For switchers the 10^{th} percentile is 4 log points worse in the model than in the data. The 90^{th} percentile of wage changes is five log points too low for stayers and eight log points for switchers.

The average switching probability in the model is 22% for the direct job changers, compared to the targeted 30% in the data.[27] Turning to the slope of the switching profile by unemployment duration, the probability to switch increases by about 22% in the model, compared to 29% in the data. The relationship is generated, because the switching probability decreases with human capital, as discussed above. The model has difficulties in matching the switching pattern by rank in the calibration: it exhibits a u-shape, compared to the monotonically decreasing pattern in the data. The reason for this is a negative correlation between beginning of period human capital and idiosyncratic productivity (the correlation coefficient is $-.07$; see footnote 24).

Figure 2.5 shows the overall distribution of realized wage changes for the four subgroups defined by direct job change (E-E) vs. job change through unemployment (E-U-E), and

[27] Given that the model features six occupations, whereas the data moment is based on 30 occupational groups, this seems a minor issue of the calibration.

Figure 2.5: Distribution of Wage Changes in Calibrated Model



Note: Density functions of observed wage changes in the model.

staying in the occupation vs. switching occupations. Consider direct job changers that stay at their occupation. Their distribution of wage changes is driven by two elements: first, their draws of η^{stay}-shocks, and second, a share of these workers moves up the human capital ladder by one step, which slightly bends the right tail outwards. Job Changers that switch occupations realize more negative wage realizations because they move down the human capital ladder. Similarly, a larger share realizes high wage gains: these workers find a particularly productive match in a different occupation (they draw from a wider distribution of productivity shocks), and thus they are willing to move down the human capital ladder.

Now, consider the distribution of wage changes realized in the model by workers that spend up to one year in unemployment. We see in Figure 2.5 that these workers move down the human capital ladder and thus the left arm of the distribution of wage changes is heavier. Compared to the data, the calibrated model overemphasizes the negative wage changes for the job changers through unemployment. In the data, the 10^{th}, 50^{th}, and 90^{th} percentiles of wage changes for the stayers and switchers are $(-.28, -.00, .25)$ and $(-.37, -.02, .31)$, respectively. The model implies wage changes of $(-.45, -.12, .09)$ and $(-.83, -.16, .15)$, respectively.

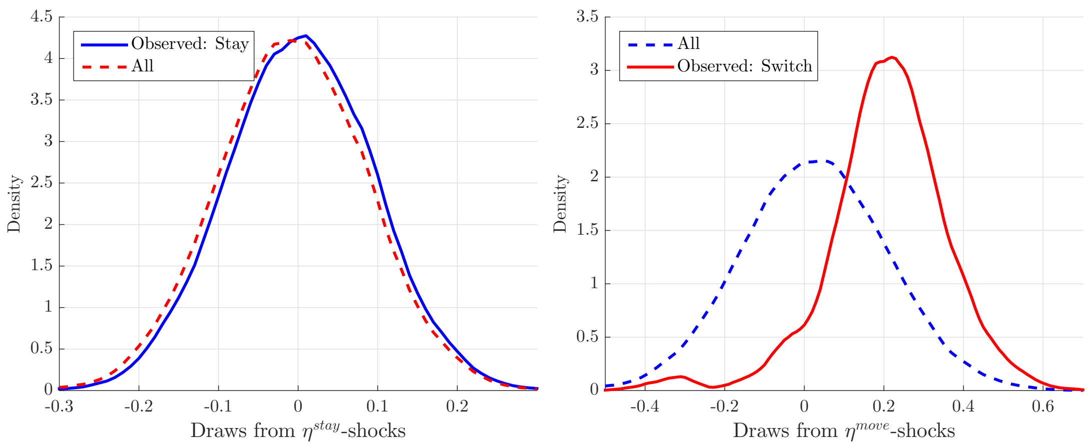
2.5.2 Choice vs. Shock and the Option Value of Switching

Roles of Underlying Productivity Shocks and Occupational Choice

Figure 2.6 shows the distribution of stochastic productivity shocks together with the distribution of the shocks that can be observed; "observed" referring to the *stay*-shocks realized by *stayers* and the *move*-shocks realized by *switchers*. Considering stayers, the distribution of observed realizations from the distribution is more skewed to the right than the distribution of η^{stay}-shocks in the population: left-tail (right-tail) events are less (more) likely to be observed than they are realized. For the distribution of η^{move}-shocks this is even more apparent. Compared to the distribution of draws from the underlying distribution, in the observed distribution the left tail collapses almost completely: switchers face the (indirect) cost of moving down the human capital ladder and thus only draws that compensate for the implied wage loss are accepted. The mass points in the left tail are the result of workers accepting a more severe human capital cut when moving to an occupation that is more distant.

Figure 2.6: Distribution of Underlying Shocks and of Realized Shocks

(a) Distribution of η^{stay} (b) Distribution of η^{move}



Note: Density functions of η^{stay}-shocks and η^{move}-shocks received by workers that decide to stay or to switch; solid lines are *observable* shocks, dashed lines are *all* shocks.

Changes of stochastic productivity play a bigger role relative to movements along the human capital ladder for switchers than for stayers: For direct job changers that stay in their occupation, the overall variance of wage changes in the calibrated model is .0128, out of which .0044 are generated by changes in human capital; for switchers these numbers are .0469 and .0284, respectively. Now, what is the role of the occupational *choice relative to underlying shocks*? To evaluate this, I disregard changes of human capital for now. Assume that one can directly observe the realized distributions of productivity shocks for switchers and stayers as displayed in figure 2.6. The variances of realized shocks turn out to be $\left(\tilde{\sigma}_{\eta}^{move}\right)^2 = .0231$ and $\left(\tilde{\sigma}_{\eta}^{stay}\right)^2 = .0084$, where tilde denotes realized changes. Compare these to the variance of underlying shocks, $\left(\sigma_{\eta}^{move}\right)^2 = .0335$ and $\left(\sigma_{\eta}^{stay}\right)^2 = .0087$. If one were to ignore selection of workers into switching and staying, and equate the observed realizations of productivity shocks to the underlying distribution, one would underestimate the variance of productivity shocks for movers by 31.0% and for stayers by 3.7%.

A second way of pinning down the importance of the selection process for the distribution of productivity changes is to calculate its role for the distribution of wage changes for *all job changers* (E-E). Assume that one knew the true dispersion of the productivity shocks and the correct share of switchers (implied by the model), p_{switch}. If selection into either group was random, one could express the distribution of productivity shocks as a mixture of Normal distributions: with probability p_{switch} a worker draws from $\mathcal{N}\left(\mu_{eta}^{move}, \left(\sigma_{\eta}^{move}\right)^2\right)$, and with probability $(1 - p_{switch})$, a worker draws from $\mathcal{N}\left(\mu_{eta}^{stay}, \left(\sigma_{\eta}^{stay}\right)^2\right)$. The implied counterfactual distribution of productivity shocks has a variance of $\left(\sigma_{\eta}^{counterfact}\right)^2 = .0137$. Compare this to the distribution of productivity shocks actually realized in the model: $\left(\sigma_{\eta}^{actual}\right)^2 = .0186$. Thus, the counterfactual distribution understates the dipersion by 26%. Put differently, the endogenous choice accounts for 26% of realized productivity changes.

The Option Value of Occupational Switching

Given that the endogenous switching decision appears to be of major relevance for realized dispersion of productivity changes, I now evaluate how much workers do prefer a world in which they can switch occupations to a world where they are exposed to occupation-related shocks? In other words, what is the utility gain that workers get from the *option of switching* in expectation of productivity shocks? I evaluate this by calculating the Compensating Variation in a counterfactual world without the option to switch occupations that is necessary to make these workers indifferent to living in the actual (model) world–while workers are facing the same shock processes for exogenous job separations, job finding, stochastic productivity, human capital accumulation, and occupational tastes.

Consider a worker who enters the period employed in occupation $o_{i,t}$, with human capital level $h_{i,t}$, and stochastic productivity $x_{i,t}$. The worker receives two productivity shocks, $\boldsymbol{\eta}_{i,t}$, and his value function is given in equation (2.10) as $V^{empl}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$. In the counterfactual world, the worker always stays in occupation $o_{i,t}$. The value functions for employed and unemployed workers are denoted by $V^{count}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$ and $V^{count-ue}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$, and shown in appendix A.2. The ex ante expected value of being employed in state $(x_{i,t}, h_{i,t}, o_{i,t})$, i.e., before the realization of the $\boldsymbol{\eta}$-shocks, is given

Table 2.4: The Option Value of Occupational Switching

	λ
Overall	0.78%
Unemployed Workers	1.25%
Employed Workers	0.73%

Note: The table shows the utility gain from switching expressed as a share of per-period Consumption, λ.

in the two worlds by

$$\widetilde{V}^{empl}\left(x_{i,t}, h_{i,t}, o_{i,t}\right) \equiv E_{\boldsymbol{\eta}} V^{empl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right)$$

and

$$\widetilde{V}^{counter}\left(x_{i,t}, h_{i,t}, o_{i,t}\right) \equiv E_{\boldsymbol{\eta}} V^{counter}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right).$$

I now calculate the per-period Consumption Compensating Variation (CCV), λ, that makes the average worker in the world without switching indifferent to the world where he can switch. Denote the state vector $(x_{i,t}, h_{i,t}, o_{i,t})$ by $s_{i,t}$. Using the stationary distribution of workers over states $s_{i,t}$ in the model with occupational switching, λ is defined implicitly by

$$\sum_j \omega_j \widetilde{V}^{empl}\left(s_{i,t} = j\right) \stackrel{!}{=} \sum_j \omega_j \widetilde{V}^{counter}\left(s_{i,t} = j; \lambda\right), \tag{2.15}$$

where $\widetilde{V}^{counter}(\bullet; \lambda)$ reflects the expected present value utility when consumption is adjusted by the factor $(1+\lambda)$ in every state, and ω_j denotes the share of workers in state $s_{i,t} = j$ in the stationary distribution. Given the homotheticity of the per-period utility function (utility is linear), λ can be calculated in closed form as

$$\lambda = \left(\frac{\sum_j \omega_j \widetilde{V}^{empl}\left(s_{i,t} = j\right)}{\sum_j \omega_j \widetilde{V}^{counter}\left(s_{i,t} = j\right)}\right) - 1.$$

Table 2.4 shows the value that workers assign to the option of switching.[28] Ex ante, workers have a utility gain from the option to switch that amounts to about 0.78% of their expected per-period consumption. Conditioning on employment state, those that enter

[28] The calculation for unemployed workers follows the same procedure as the one for employed workers described in the text.

the period as unemployed, assign a higher value of about 1.25% of per-perid consumption to the availability of switching–which is to be expected, given that unemployed workers switch more often. The Compensating Consumption Variation for employed workers is 0.73%.

2.6 Conclusion

In this chapter, I take a step in disentangling the role played by productivity *shocks* and occupational *choices* for observed wage dynamics. I first show empirically that the distribution of *realized* wage changes varies systematically between occupation switchers and stayers. I then show that switching occupations is an empirically relevant phenomenon among job changers, and that the probability of switching, (i), correlates negatively with relative wage in the old job, and, (ii), increases with the duration of unemployment. I then set up a structural model of the labor market featuring multiple occupations. The calibrated model is consistent with the documented patterns of occupational switching and wage changes and serves two purposes. First, it allows me to evaluate the relative role of occupational choice for productivity changes. In the model, if one were to mistake the observed distribution of productivity changes (after controlling for human capital in the model) realized by switchers (stayers) for the underlying shock distributions, one would make an error of 31% (4%) in terms of the variance. Overall, the endogenous choice of occupations accounts for about 26% of realized productivity changes of workers that change jobs without experiencing an unemployment spell. Second, workers value the option of switching occupations, because it allows them to react to negative shocks in the current occupation and to realize good offers related to a different career. The utility gain from the option to switch occupations corresponds to 0.78% of per-period consumption for the average worker; given that unemployed workers utilize the option to switch more often, their utility gain is higher (1.25%) than the gain for employed workers (0.73%).

Chapter 3

Labor Income Risk in Germany Over the Business Cycle

This chapter is based on Busch and Ludwig (2016).[1]

3.1 Introduction

Understanding how individual incomes vary over the business cycle is of major importance for economic policy, e.g., for the design of stabilization policies. Capturing the intuitive notion that downside labor income risk of workers is increasing in a recession with an income process featuring a countercyclical variance might, however, be misleading. Such a process implies that during a recession the probabilities of both, an income drop as well as a rise of income, are higher. The latter implication seems wrong. In order to allow for the possibility of higher downside risk along with constant (or lower) upside chances during a recession, one must take the third moment of the distribution, the skewness, into account. An income process with countercyclical left-skewness of individual income risk implies that in a recession the probability of a drop in income is higher—as also implied by a countercyclical variance—and that the probability of an increase of income is unchanged (or smaller)—unlike implied by a countercyclical variance.

In this chapter we address this matter by developing a novel parametric approach to estimate the relationship between idiosyncratic labor income risk over the business cycle. We analyze the cyclicality of the distribution of idiosyncratic labor income shocks, i.e., shocks to income conditional on observable characteristics such as age and education. We do so by first adopting the standard approach to decompose labor income into a

[1]We thank Helge Braun for numerous helpful discussions and Kjetil Storesletten for insightful comments.

deterministic and a stochastic component. The stochastic component in turn is composed of a fixed effect as well as a persistent and a transitory shock to income. The distributions of these two components are parameterized by the respective variance and skewness. In addition, the moments of the persistent shock are assumed to be contingent on the aggregate state of the economy, i.e., whether the economy is in a recession or in a boom.

Our parametric estimation procedure allows for identification of all these moments of the shock distribution. Specifically, we derive closed form expressions for the (state contingent) variance and skewness and base identification on a standard Generalized Method of Moments (GMM) approach. To achieve this, we extend the influential method of Storesletten et al. (2004) (STY) who estimate an income process with a state-contingent variance of the persistent income shock. They find that the variance is higher in recessions which has been labelled a *counter-cyclical variance* effect.[2] STY base identification of the state contingent variance on the observation that persistent shocks accumulate over an individual's life-cycle such that the distribution of labor incomes observed for a given cohort widens as this cohort ages. This implies that cohorts that experienced different macroeconomic histories will feature different cross-sectional age-specific variances of labor incomes if the variance of income shocks varies over the business cycle.

We extend their framework and analyze how the skewness of the innovation accumulates when a cohort ages, using the same idea for identification (i.e., our identification is based on the notion that the accumulated skewness differs across cohorts if these cohorts experienced different macroeconomic histories). As a measure for skewness we use the third central moment of a distribution. Importantly, we do not base identification on the standard measure of skewness, which is the third centralized moment normalized by the variance of the distribution. Since we avoid this normalization, there is no interference between our estimates of the variance and the skewness of earnings shocks.

We apply our empirical approach to labor incomes from the German Socio-Economic Panel (SOEP) which is similar to the US Panel Study of Income Dynamics (PSID). We base our estimation on gross labor earnings of males aged 25 to 60, that currently live in West Germany and did not immigrate after age 10, as well as on two measures of household level labor incomes. The first is based on gross labor income of household head and spouse, the second on post government net labor income.

Our results establish three important insights on labor income risk in Germany. First, the variance of log labor earnings shocks of males is countercyclical. Hence, the variance of log earnings is higher in recessions than it is in booms. The increase in the variance of log

[2]This terminology has been introduced in the macroeconomic asset pricing literature, see Mankiw (1986), Constantinides and Duffie (1996), or Storesletten et al. (2007).

earnings in recessions is due to an increase of the left skewness: negative log labor earnings realizations are more likely in recessions than positive ones. Second, there is insurance against transitory income shocks at the household level, but not against permanent shocks. Relative to male earnings, the variance of transitory income shocks decreases but the moments for permanent shocks are (almost) unchanged. Third, the German tax and transfer system insures against both transitory and permanent earnings shocks. For post government earnings (after taxes and transfers) the distribtuion of transitory shocks is further compressed relative to pre government earnings and the cyclicality of earnings shocks is gone.

Related Literature

On the empirical side, several studies analyze patterns of residual income inequality over time and over the lifecycle. Examples for the US are Moffitt and Gottschalk (2002) and Heathcote et al. (2010), who document the development of residual inequality over the past three decades. Trends in income inequality in Germany are studied, e.g., by Dustmann et al. (2009) using administrative data and Fuchs-Schündeln et al. (2010) using data from the German Socioeconomic Panel (SOEP). For Germany, Bayer and Juessen (2012) document a slightly procyclical variance of wage risk. In contrast to us, they focus on wages.

Recently, Guvenen et al. (2014) stress the importance for estimating higher order moments of income processes. Using an extensive administrative dataset from US social security records they challenge the evidence by STY that cyclicality is solely in terms of the variance. Their findings instead suggest that the left-skewness of individual income risk increases in a recession, whereas the variance does not change. This motivates our approach. Methodologically, we differ from Guvenen et al. (2014) in that we superimpose more parametric structure, as in STY. Hence, our approach is well suited for typically easily available smaller data sets.

In follow-up work to Guvenen et al. (2014), Guvenen et al. (2016) show that most individuals experience very small earnings changes and a considerable number of workers very large ones. Hence, the kurtosis of labor earnings is much higher than the conventional assumption of log normality implies. Given the relatively small sample size of the SOEP, we do not estimate the kurtosis (and how it varies over the cycle). It is, however, straightforward to extend our empirical approach by additional moments for the kurtosis. To achieve independence of the variance, this should again be based on the fourth non-standardized moment of the distribution. Also, notice that our estimates of the variance and skewness (and how these moments vary over the cycle) are not affected by omitting the kurtosis.

All the aforementioned papers on earnings risk have in common that using the estimates in macroeconomic models requires a two-step procedure. As a first step, the estimation is carried out. In a second step, the estimates are approximated, cf., e.g., Guvenen et al. (2016) and McKay (2016). De Nardi et al. (2016) suggest to avoid this by directly estimating a Markov process on the data.

An important difference between this chapter and these recent papers on higher moment income risk[3] is that we adopt the tradition in the labor/consumption literature to distinguish between transitory and permanent shocks to income (Deaton, 1992). This distinction is crucial to understand the disjuncture between consumption and earnings distribution and to study how households are insured against permanent and transitory shocks (cf. Blundell et al., 2008b or Kaplan and Violante, 2010). Our application establishes such insurance within the household and through the government. These findings share similarities with those of Blundell et al. (2014), who use Norwegian data, without looking at higher moments though.

The remainder of this chapter is structured as follows. Section 3.2 presents our empirical approach, discusses the moment conditions used to identify the parameters of the earnings process and provides intuition for identification. Section 3.3 describes the application of our approach to German earnings data from the SOEP. We start by describing the data and by defining business cycles and move on to illustrate how variance and skewness at different ages depend on histories, i.e., the number of recessions a cohort has worked through. We then present our main estimation results. Finally, Section 3.4 concludes.

3.2 Empirical Approach

3.2.1 Overview

The individual income process is specified in a way that allows us to separately identify cyclicality in the variance and skewness of innovations to the persistent component. Our identification strategy is an extension of the approach proposed by Storesletten et al. (2004). The basic idea is to exploit how the distribution of persistent idiosyncratic shocks accumulates over time: if the income process is persistent, then, as a cohort ages, the cross-sectional income distribution at any age, can be characterized by the sequence of shocks experienced by the cohort's members. If the variance of the innovation depends on

[3] In addition to our focus on how idiosyncratic risk varies over the business cycle, which only some of the higher moment income risk papers share.

the aggregate state of the economy, then the cross-sectional income variance at a certain age differs between two cohorts if these cohorts went through different macroeconomic histories. Storesletten et al. (2004) allow for two states of the variance—one in contractions and one in expansions—and classify each year as either an expansion or a contraction.

We extend their framework by analyzing how the skewness of the innovation accumulates when a cohort ages. As a measure for skewness we use the third central moment of a distribution. Given our specification of the income process, we derive closed-form expressions for the variance and skewness of income and develop a Generalized Method of Moments (GMM) estimator to identify all parameters of interest. In addition to variance and skewness, we consider the covariance and a measure of coskewness in our construction of moment conditions. These moments allow us to separately identify variance and skewness of transitory and permanent shocks and of the fixed component, as will be discussed below.

The key advantage of using central moments in the estimation is that we can remain agnostic about the exact distribution of the stochastic components in the estimated earnings process. However, measurement of central moments could be problematic given the available sample size, because the measures are sensitive to outliers. Percentile based measures are more robust. However, were we to use percentile based moments, we would have to estimate the process using a Method of Simulated Moments approach—and therefore take a stand on density functions. In order to evaluate the importance of potential small sample biases, we compare the age profiles of the applied central moments to the profiles of the percentile based counterparts to these moments. We find that qualitatively the age profile is the same, which encourages our choice of central moments.

3.2.2 The Income Process

We impose the following income process, which is commonly used in the literature. The (log) income of household i of age h in year t is

$$y_{ith} = f(\mathbf{X}_{ith}, Y_t) + \tilde{y}_{ith}, \tag{3.1}$$

where $f(\mathbf{X}_{ith}, Y_t)$ is the *deterministic* part of income, i.e., the part that can be explained by observable individual and aggregate characteristics, $\mathbf{X}_{ith}$ and Y_t, respectively, and $\tilde{y}_{ith}$ is the unexplained part of income that is assumed to be orthogonal to $f(\mathbf{X}_{ith}, Y_t)$. We consider age, education, and the household size as elements of $\mathbf{X}_{ith}$. More specifically, the deterministic component $f(\mathbf{X}_{ith}, Y_t)$ is a linear combination of a cubic in age h and the log of household size, $hhsize_{ith}$. The aggregate effects are captured by a time-varying intercept and the education premium is allowed to vary over time following a quadratic function:

$$f\left(\mathbf{X}_{ith}, Y_t\right) = \beta_{0t} + f_h\left(h\right) + I_{e_{it}=c} f_{EP}(EP) + \beta^{size}\log\left(hhsize_{ith}\right) \tag{3.2}$$

where $f_h\left(h\right) = \beta_1^{age}h + \beta_2^{age}h^2 + \beta_3^{age}h^3$ and $f_{EP}(EP) = \beta_0^{EP} + \beta_1^{EP}t + \beta_2^{EP}t^2$.

Residual income $\tilde{y}_{ith}$ is the main object of interest in the analysis. We model $\tilde{y}_{ith}$ as the sum of three components: a fixed effect χ_i, a persistent component z_{ith}, and an iid transitory shock ε_{ith}. The persistent component is modeled as an AR(1) process with innovation η_{ith}.

$$\tilde{y}_{ith} = \chi_i + z_{ith} + \varepsilon_{ith},\ \text{where } \varepsilon_{ith} \underset{iid}{\sim} F_\varepsilon\left(0, m_2^\varepsilon, m_3^\varepsilon\right),\ \chi_i \underset{iid}{\sim} F_\chi\left(0, m_2^\chi, m_3^\chi\right) \tag{3.3a}$$

$$z_{ith} = \rho z_{t-1h-1} + \eta_{ith},\ \text{where } \eta_{ith} \underset{iid}{\sim} F_\eta\left(0, m_2^\eta\left(s\left(t\right)\right), m_3^\eta\left(s\left(t\right)\right)\right), \tag{3.3b}$$

where $F_{\chi/\varepsilon/\eta}\left(\cdot\right)$ denotes the density functions of χ, ε_{ith} and η_{ith}, respectively. The fixed effect and both shocks are mean zero and $m_2^{\chi/\varepsilon/\eta}$ and $m_3^{\chi/\varepsilon/\eta}$ are the second and third moments, respectively. The second and third moments of the persistent shock are allowed to depend on the aggregate state of the economy in period t, denoted by $s\left(t\right)$.

3.2.3 The GMM Approach

The common approach in estimating (3.1) is to perform the estimation in two steps, where the first step estimation yields residuals and the second step fits the stochastic process (3.3) to cross-sectional moments of the distribution of residual (log) income. The imposed process implies the following moments of the distribution of residual income at age h in year t:

$$m_2\left(\tilde{y}_{ith};\theta\right) = m_2^\chi + m_2^\varepsilon + \textstyle\sum_{j=0}^{h-1}\rho^{2j} m_2^\eta\left(s\left(t-j\right), h-j\right) \tag{3.4a}$$

$$m_3\left(\tilde{y}_{ith};\theta\right) = m_3^\chi + m_3^\varepsilon + \textstyle\sum_{j=0}^{h-1}\rho^{3j} m_3^\eta\left(s\left(t-j\right), h-j\right) \tag{3.4b}$$

$$cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right) = m_2^\chi + \rho\textstyle\sum_{j=0}^{h-1}\rho^{2j} m_2^\eta\left(s\left(t-j\right), h-j\right) \tag{3.4c}$$

$$csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right) = m_3^\chi + \rho\textstyle\sum_{j=0}^{h-1}\rho^{2j} m_3^\eta\left(s\left(t-j\right), h-j\right), \tag{3.4d}$$

where $\theta = \left(m_2^\chi, m_3^\chi, m_2^\varepsilon, m_3^\varepsilon, m_2^{\eta,E}, m_2^{\eta,C}, m_3^{\eta,E}, m_3^{\eta,C}\right)$ is a vector collecting the 8 second-stage parameters. $m_2\left(\tilde{y}_{ith};\theta\right)$ and $m_3\left(\tilde{y}_{ith};\theta\right)$ denote the second and third central moment; $cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)$ and $csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)$ denote the covariance and a measure of coskewness between $\tilde{y}_{ith}$ and $\tilde{y}_{it+1h+1}$. Coskewness is measured here as the covariance between $\tilde{y}_{ith}^2$ and $\tilde{y}_{it+1h+1}$, i.e., $csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right) \equiv cov\left(\tilde{y}_{ith}^2, \tilde{y}_{it+1h+1};\theta\right)$. The two covariance terms allow to separately identify the moments of χ and ε.

Before implementing the second stage estimator, we impose more structure on the time dependency of $F_\eta(\cdot)$. Variance and skewness of the persistent innovation η_{it} are modelled as two state processes: $m_2^\eta(\cdot)$ and $m_3^\eta(\cdot)$ take on two possible values each, depending on the aggregate state $s(t)$, which is either an expansion or a contraction. To this end, define the indicator variable $I_{t=\text{expansion}}$ to be equal to 1 if year t is an expansion (denoted by E) and to be equal to 0 if year t is a contraction (denoted by C). We then have:

$$m_2^\eta(s(t)) = I_{s(t)=E} m_2^{\eta,E} + \left(1 - I_{s(t)=E}\right) m_2^{\eta,C} \tag{3.5a}$$

$$m_3^\eta(s(t)) = I_{s(t)=E} m_3^{\eta,E} + \left(1 - I_{s(t)=E}\right) m_3^{\eta,C} \tag{3.5b}$$

Small sample size can lead to central moments being measured imprecisely. We therefore calculate moments for $H_g < H$ age groups. Mean independence of shocks implies for the theoretical counterparts that:

$$\begin{aligned} m_k\left(\tilde{y}_{ith_g};\theta\right) &= \frac{1}{\sum_{h\in h_g} N_{h,t}} \sum\nolimits_{h\in h_g} N_{h,t} m_k\left(\tilde{y}_{ith};\theta\right) \text{ for } k = 2,3 \\ cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)_{h\in h_g} &= \frac{1}{\sum_{h\in h_g} N_{h,t}} \sum\nolimits_{h\in h_g} N_{h,t} cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right) \\ csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)_{h\in h_g} &= \frac{1}{\sum_{h\in h_g} N_{h,t}} \sum\nolimits_{h\in h_g} N_{h,t} csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right). \end{aligned}$$

Given H_g age groups and T years of observations we obtain $H_g \times T$ cross-sectional measures of variance and skewness each, and $H_g \times (T-1)$ estimates of covariance and coskewness, i.e., $2 \times H_g \times T + 2 \times H_g \times (T-1)$ empirical moments. The moment conditions employed in the GMM estimation read as follows:

$$E\left[m_2\left(\tilde{y}_{ith_g}\right) - m_2\left(\tilde{y}_{ith_g};\theta\right)\right] = 0 \tag{3.6a}$$

$$E\left[m_3\left(\tilde{y}_{ith_g}\right) - m_3\left(\tilde{y}_{ith_g};\theta\right)\right] = 0 \tag{3.6b}$$

$$E\left[cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1}\right)_{h\in h_g} - cov\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)_{h\in h_g}\right] = 0 \tag{3.6c}$$

$$E\left[csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1}\right)_{h\in h_g} - csk\left(\tilde{y}_{ith}, \tilde{y}_{it+1h+1};\theta\right)_{h\in h_g}\right] = 0, \tag{3.6d}$$

where the first term in each line is the empirically calculated moment, e.g., the variance of residual earnings in year 2000 of workers in age group 2. The second term in each line is the theoretical counterpart implied by a specific combination of parameters in θ. We define 7 age groups: 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-60. In the estimation we impose that each worker i enters the labor market at age 25 in some year t, draws a fixed effect χ_i from the distribution $F_\chi\left(0, m_2^\chi, m_3^\chi\right)$, which does not vary over time, and draws the first realizations of transitory and permanent shocks, ε_{it} and η_{it}, from the distributions $F_\varepsilon\left(0, m_2^\varepsilon, m_3^\varepsilon\right)$ and $F_\eta\left(0, m_2^\eta\left(s\left(t\right)\right), m_3^\eta\left(s\left(t\right)\right)\right)$. Given a classification of years as expansions or contractions, we can then use (3.6) together with (3.4) to estimate the parameters of the income process.

3.2.4 Identification

The use of cross-sectional moments for identification allows to exploit macroeconomic information that predates the micro panel, thereby incorporating more business cycles in the analysis than covered by the sample, as pointed out and elaborated on by STY.

In order to understand how identification works, consider the persistent component of the income process, cf. equation (3.3b): the variances of the innovations accumulate as a cohort ages, as can be seen from the theoretical moment in equation (3.4a). If the innovation variance is higher in contractionary years, then a cohort that lived through more contractions as it reaches a given age will have a higher income variance at that age than a cohort that lived through fewer contractions has at the same age.

Our extension of STY is based the insight that a similar accumulation holds for the skewness, as seen in equation (3.4b). If the probability of a large negative/positive income shock would be higher/lower for the average worker during a macroeconomic contraction, then the skewness of the shock in a contractionary period would be smaller (more negative) than in an expansion, i.e., $m_3^{\eta,C} < m_3^{\eta,E}$. Comparing again two cohorts when they reach a certain age, this would imply a more negative cross-sectional skewness for the cohort that worked through more recessions.

As seen in (3.4a), the sum $\left(m_2^\chi + m_2^\varepsilon\right)$ is identified as the intercept of the variance profile over age. The same holds for $\left(m_3^\chi + m_3^\varepsilon\right)$ in (3.4b), which is identified via the age profile of skewness. Considering the sum in (3.4a), we see that the magnitude of the increase of the cross-sectional variance over age identifies the variance of persistent shocks. The difference between $m_2^{\eta,C}$ and $m_2^{\eta,E}$ is identified by the difference of the cross-sectional variance of different cohorts of the same age. Likewise, the difference between $m_3^{\eta,C}$ and $m_3^{\eta,E}$ is identified by the difference of the cross-sectional skewness of different cohorts.

The last piece of information for identification comes from considering the expressions for variance and covariance in equations (3.4c) and (3.4a). It becomes immediately apparent that the difference between the two expressions identifies m_2^χ separately from m_2^ε. Likewise, the difference between the expressions for skewness and coskewness, equations (3.4b) and (3.4d), identifies m_3^χ separately from m_3^ε.

3.3 Application: Earnings Risk of German Households

3.3.1 Data and Sample Selection

The Socio-Economic Panel (SOEP) is a survey based panel study covering the years 1984 to 2013. It was initiated with about 10,000 individuals in 5,000 households in 1984 and covers about 18,000 (10,500) individuals (households) in 2013. We define household level income variables as follows. Household labor income before taxes is calculated as the sum of head and spouse annual labor income. Labor income is the sum of income from first and second jobs, 13th and 14th monthly salaries, Christmas and vacation bonuses, profit sharing and other bonuses. 50% of income from self-employment is assigned to labor income.

Post-government income is defined as household labor income plus transfers minus taxes. Transfers are aggregated over all household members and include pensions (old age; disability; widows; orphans; or other), maternity benefit, student grants, unemployment benefits, unemployment assistance (before 2005), subsistence allowance, child allowance, unemployment benefit II (since 2005). Taxes are provided in the SOEP as estimated from TAXSIM at the household level. All nominal values are deflated with the CPI.

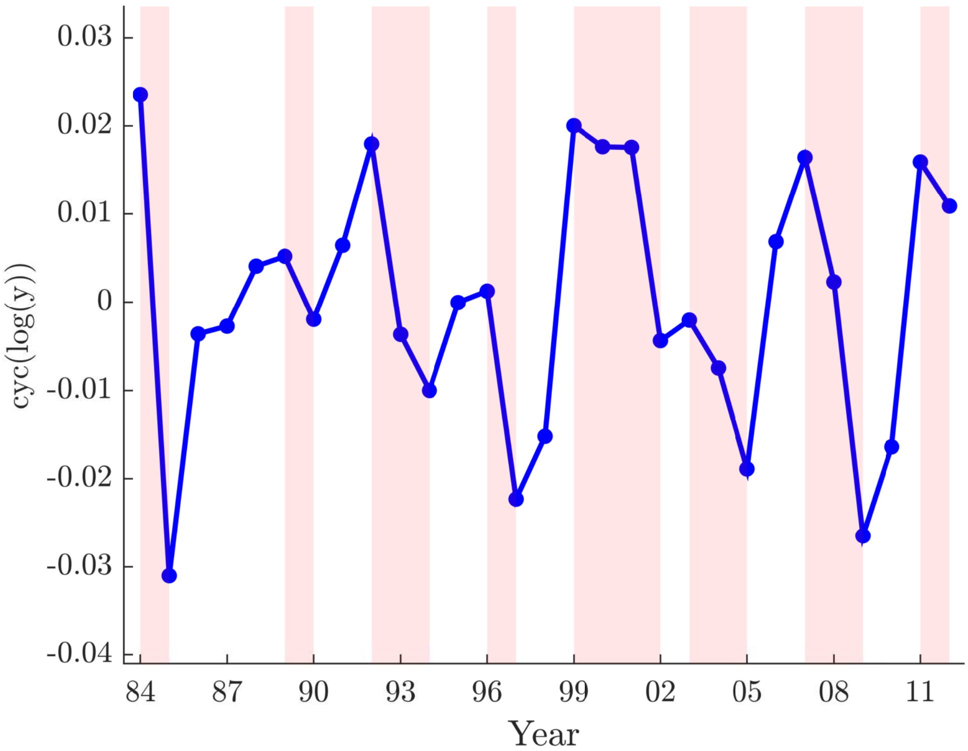
We exclude SOEP subsamples D and G, which oversample immigrants and high income households, respectively, and apply the following sample selection criteria. We select males between 25 and 60 years of age, that currently live in West Germany, and did not immigrate after age 10. Labor earnings needs to be above a constant threshold, which is defined as the income from working 520 hours for three year 2000 Euros. A household is in the household sample if it is comprised of at least 2 adults. The age restriction applies to the household head and the income threshold needs to be exceeded by the minimum of male labor earnings and household post-government income.

3.3.2 Defining Business Cycles

In order to implement the estimator we need to classify years as contractions or expansions. We initiate the classification with peak and trough dates from ECRI[4], which is based on NBER methodology. Given the sluggish synchronization of labor market outcomes with the macroeconomic indicators that ECRI takes into account, we expand the dating based on mean earnings of males in the SOEP, as shown in Figure 3.1. For the classification of

[4]The Economic Cycle Research Institute classifies business cycles based on several macroeconomic indicators: https://www.businesscycle.com/ecri-business-cycles/international-business-cycle-dates-chronologies.

Figure 3.1: Business Cycle Dating Based on Mean Earnings



Note: Figure shows the cyclical component of HP-filtered (mean) male earnings in the SOEP; smoothing parameter for the HP-filter is 6.25.

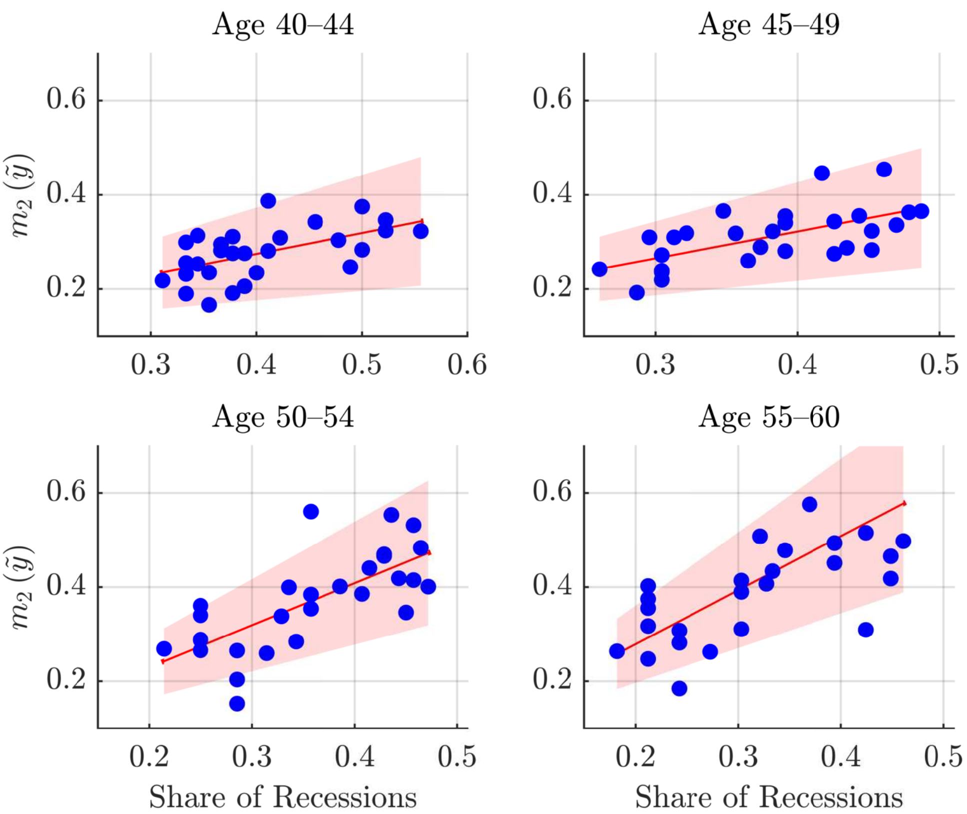
years in the pre-sample period, we use the unemployment rate, which during the sample time is highly correlated with male earnings.

Given the dating of peaks and troughs, we characterize years as expansions and contractions as follows. A year is classified as a contraction if: (i) it completely is in a contractionary period which is defined as the time from peak to trough, (ii) if the peak is in the first half of the year and the contraction continues into the next year, (iii) if a contraction started earlier and the trough is in the second half of the year. All years that are not classified as contraction are classified as expansions.

3.3.3 Intuition Behind the Estimator

This section uses information from the data to discuss the intuition behind the estimator, thereby relating back to our discussion on identification in Subsection 3.2.4. Figure 3.2 shows the variance, m_2, of the cross-sectional distribution of male labor earnings for different age groups as a function of the share of contractionary years a cohort lived through. For each age group, the higher the share of contractions a cohort went through, the more dispersed is the cross-sectional earnings distribution. Recall that this is an implication of the earnings process if $m_2^{\eta,C} > m_2^{\eta,E}$, i.e., if the variance of permanent shocks

Figure 3.2: Intuition: Cross-sectional Second Moment

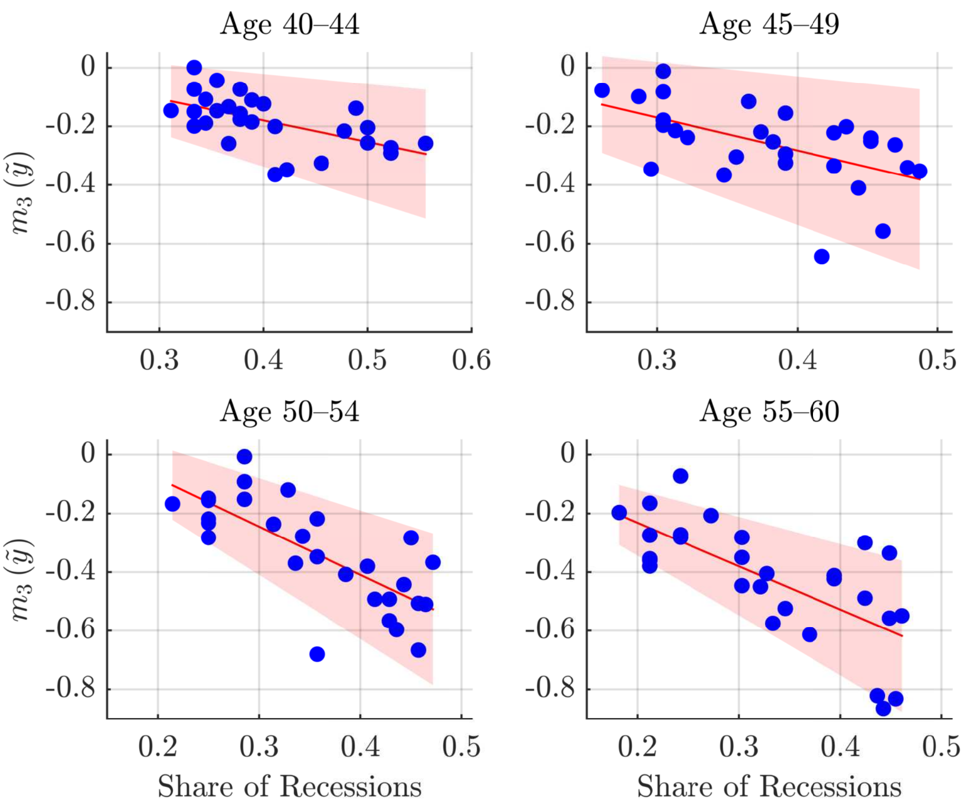


Note: The x-axis of each figure shows the share of contractions in all years a cohort went through at a certain age. The y-axis shows the second central moments for different cohorts at different ages.

is countercyclical, cf. equation (3.4a). The increasing variance in the share of recessions therefore identifies $m_2^{\eta,C}$ and $m_2^{\eta,E}$. Similarly, Figure 3.3 shows the third central moment of the cross-sectional earnings distribution as a function of the share of contractions. For each age group, we observe a clear downward-sloping pattern, which is implied by the earnings process if $m_3^{\eta,C} < m_3^{\eta,E}$, i.e., if the skewness is procyclical, cf. equation (3.4b). The decreasing skewness in the share of recessions therefore identifies $m_3^{\eta,C}$ and $m_3^{\eta,E}$.

Fitting a linear regression in each figure suggests a statistically significant difference between the distribution of permanent shocks in contractions and expansions. Table 3.1 shows the coefficients. This is indeed what we estimate below in Subsection 3.3.4. Finally, recall from our discussion in Subsection 3.2.4 how the moments of the transitory income shock, m_2^{ε} and m_3^{ε} can be identified given the equations in (3.4). To illustrate identification of these two terms, we compute the difference between variance and covariance in each cross-section and take the average over all years. This suggests that $m_2^{\varepsilon} \approx 0.0815$, cf. equations (3.4a) and (3.4c). Similarly, calculating the difference between skewness and coskewness in each cross-section and taking the average over all years suggests that $m_3^{\varepsilon} \approx$

Figure 3.3: Intuition: Cross-Sectional Third Moment



Note: The x-axis of each figure shows the share of contractions in all years a cohort went through at a certain age. The y-axis shows the third central moments for different cohorts at different ages.

−0.1083. These values are indeed very close to what the estimation yields in Subsection 3.3.4 to which we turn next.

Table 3.1: Central Moments as Function of Share of Contractions

	$m_2(\tilde{y})$	$m_3(\tilde{y})$
Age 40–44	0.45	–0.74
	(3.54)	(–3.65)
Age 45–49	0.57	–1.13
	(4.27)	(–3.50)
Age 50–54	0.90	–1.65
	(5.37)	(–5.87)
Age 55–60	1.15	–1.48
	(5.48)	(–5.19)

Note: Each cell shows the slope coefficient of the respective fitted line in figures 3.2 and 3.3. T-statistics are in parantheses.

3.3.4 Estimation Results: Cyclical Income Risk

Estimating income processes, we started with a specification where we estimated the persistence of the persistent income shock process, ρ. It turned out that ρ was not significantly different from 1. We therefore restrict $\rho = 1$, hence η is a permanent shock and z is the permanent income component.

Our main estimates under this parametric restriction are summarized in Table 3.2, showing the point estimates of all parameters along with the 5^{th} and 95^{th} percentile of 250 bootstrap draws for three different specifications: male earnings, household pre government (before taxes and transfers) and household post government (after taxes and transfers) earnings. In all models, each moment in (3.6a) to (3.6d) is weighted equally, reflecting insights of Altonji and Segal (1996), who show that the identity weighting matrix dominates the asymptotically optimal weighting matrix in small samples. We apply a block bootstrap procedure in which we resample individuals—thereby preserving the autocorrelation structure of the original sample.

As a first observation, notice that the moments of the fixed effect, m_2^{χ} and m_3^{χ}, are very imprecisely estimated in all models. We therefore put no emphasis on the interpretation of these estimates. One reason for this imprecision might be that the fixed effect estimates take up cohort effects that are otherwise missing from our specification of the income process.

More important is the interpretation of the variance and skewness terms for the transitory and permanent earnings shocks which yield a number of interesting insights when moving across the different models. We start with the results for male earnings. Observe that the central moments estimated for the transitory shock, m_2^{ε} and m_3^{ε}, are at 0.0718 and-0.1, respectively, thereby coming very close to what we estimate in our illustration in the preceding Subsection 3.3.3. Accordingly, transitory income shocks are left-skewed: negative shock realizations have more weight than positive ones.

Next, notice that the variance of the permanent income shock features a strong countercyclicality—$m_2^{\eta,C} = 0.018$ and $m_2^{\eta,E} = 0.0005$ with the difference being highly significant. Our estimates of the skewness show that this countercyclicality of the variance is due to a procyclical skewness—$m_3^{\eta,C} = -0.0243$ and $m_3^{\eta,E} = 0.0037$, with both estimates significantly different from zero and from each other. Accordingly, in contractions negative log earnings realizations are more likely than positive ones. In expansions, while our estimates suggest a positive skewness, the point estimate is very small. Hence, the distribution of permanent shocks is estimated to be almost symmetric in expansions.

Moving from male earnings to household pre government earnings, we notice that there is insurance against shocks at the household level. Both the variance and the skewness of

Table 3.2: Estimation Results

m_2^χ	m_2^ε	m_3^χ	m_3^ε
Male Earnings			
.1180	.0718	$-.0219$	$-.1000$
(.0661; .1631)	(.0651; .0793)	(-0.0838; 0.0350)	($-.1081$; $-.0853$)
Household Pre-Government Earnings			
.0927	.0534	.0199	$-.0613$
(.0630; .1213)	(.0479; .0585)	($-.0193$; .0672)	($-.0700$; $-.0517$)
Household Post-Government Earnings			
.0661	.0427	$-.0149$	$-.0471$
(.0437; .0865)	(.0380; .0461)	($-.0540$; $-.0149$)	($-.0530$; $-.0395$)

$m_2^{\eta,E}$	$m_2^{\eta,C}$	$m_3^{\eta,E}$	$m_3^{\eta,C}$
Male Earnings			
.0005	.0181	.0037	$-.0243$
(.0005; .0010)	(.0108; .0245)	(.0002; .0073)	($-.0369$; $-.0170$)
Household Pre-Government Earnings			
.0022	.0157	$-.0014$	$-.0189$
(.0005; .0044)	(.0082; .0176)	($-.0043$; .0007)	($-.0231$; $-.0107$)
Household Post-Government Earnings			
.0050	.0024	$-.0025$	$-.0055$
(.0036; .0064)	(.0005; .0051)	($-.0045$; $-.0004$)	($-.0070$; $-.0023$)

Note: Table shows estimated moments for the three specifications described in the text. Parantheses show the 5^{th} and 95^{th} percentile of 250 bootstrap draws.

transitory earnings shocks decrease (in absolute terms) relative to male earnings. However, the estimates also show that there is no insurance against permanent shocks at the household level. The estimates of the variance and skewness in both contractions and expansions are not statistically different from what we find for male earnings. Hence, also for household pre government earnings, negative log earnings realizations are more likely than positive ones in contractions and the distribution of permanent shocks is estimated to be almost symmetrical in expansions.[5]

[5] The estimate of the skewness in expansions is now statistically indifferent from zero, but the point

Finally, when considering household post government earnings, both variance and skewness of transitory income shocks decrease further.[6] Also, the cyclicality of permanent shocks is gone. The variance in expansions is not statistically different from what we estimate for pre government earnings, but the variance in contractions decreases strongly and is no longer statistically different from the variance in expansions. Likewise, the skewness in contractions of permanent shocks decreases strongly when moving from pre to post government earnings and is statistically indifferent from the skewness in expansions. Now, the point estimates of the skewness in both states is small so that the distribution of permanent shocks is almost symmetric in contractions and expansions.

3.4 Conclusion

This chapter develops a new parametric estimator of higher moment income risk. We show how to use information on pre-data economic booms and recessions to identify how the variance and the skewness vary over the business cycle. We implement this by a Generalized Method of Moments estimator.

We apply our method to German earnings data. We show that permanent income shocks to male earnings exhibit strong countercyclicality, whereby the higher variance of male earnings in recessions is due to the fact that negative log income realizations are more likely in recessions than positive ones. We also establish that there is insurance against transitory earnings shocks at the household level and against transitory and permanent income shocks through the German tax and transfer system. In addition, according to our estimates, the cyclicality of earnings risk is gone for household post government earnings.

In this chapter, we focus on the second and third moment of transitory and permanent shocks to the earnings distribution. Recent work by Guvenen et al. (2016) emphasizes the importance of the fourth moment, the kurtosis. It is straightforward to extend our method to including higher moments. For reasons of data limitations (we apply our method to a relatively small panel data set, the German Socioeconomic Panel, SOEP), we have not approached this. However, because we employ non-standardized moments, our estimates of the skewness are independent of our estimates of the variance. Likewise, omitting the kurtosis does not affect our estimates for variance and skewness of earnings shocks.

estimate for males was also very small.

[6]The confidence intervals for the skewness of transitory shocks overlap slightly between pre and post government household earnings.

Chapter 4

Asymmetric Business Cycles and Government Insurance

This chapter is based on Busch et al. (2016).[1]

4.1 Introduction

This chapter studies how higher-order income risk varies over the business cycle as well as the extent to which such risks can be smoothed within households or with government social insurance policies. By higher-order income risk, we refer to risks that are captured by not only the variance of income shocks, but also their skewness and kurtosis. These higher order moments of the data can be a major source of risk for individuals as we show in this chapter.

To provide a broad perspective on these questions, we study panel data on individuals and households from the United States, Germany, and Sweden, covering more than three decades of data for each country. It is useful to begin by putting our analysis in context. A broad range of empirical evidence indicates that idiosyncratic income risk rises in recessions. Earlier work in the literature was limited by the small sample size and time span on the available survey-based panel datasets, such as the Panel Study of Income Dynamics (PSID), forcing researchers to make parametric assumptions to obtain identification. One widely used assumptions that is common in the literature is that shocks to earnings are Gaussian and, therefore, its changes are bound to be symmetric. Restricting attention to the changes in the mean and variance of income shocks, earlier studies concluded that

[1]We thank participants of the following conferences and workshops (all in 2015) for helpful comments: the SED in Warsaw, the ESWC in Montréal, the NBER SI, the 9^{th} Nordic Summer Symposium in Macroeconomics in Smögen, the EEA in Mannheim and the CESifo Conference on Macroeconomics and Survey Data in Munich.

the variance of income shocks is countercyclical (e.g., Storesletten et al., 2004). In recent work, Guvenen et al. (2014) used a very large panel dataset on earnings histories of a representative sample of 10% of all US working-age males from the U.S. Social Security Administration (SSA) records. Their large sample size, with millions of observations, allows for identification of changes in an unrestricted sense—without parametric assumptions. They found that the variance of income shocks is very stable over time and is robustly acyclical, whereas the skewness of shocks varies significantly over time in a procyclical fashion. This suggests that the changes in labor income risks in recessions and expansions are rather asymmetric.

Despite important advantages, the SSA data also have three shortcomings: (i) earnings data are available only for individuals, and it is not possible to link household members to each other, (ii) no information is available on taxes and transfers (unemployment insurance, welfare payments, gifts, etc.), and (iii) no information is available on skills/education. Furthermore, Guvenen et al. (2014) focus on males with no corresponding information on women.

This chapter makes two contributions. First, applying non-parametric techniques and using robust statistics, we document that the overall dispersion of individual labor earnings growth is flat and acyclical in all three countries, whereas the left-skewness of shocks is strongly countercyclical. These findings are robust across gender, skill groups, private/public sector employment and occupation. Furthermore, we show (using data for Germany) that these results are primarily driven by changes in wages and not in hours. Moreover, we show that applying the same method to both survey and administrative data (the PSID and SSA for the U.S. and SOEP and SIAB for Germany) yields the same substantive conclusions.

Second we find that insurance provided within households or by the government plays an important role in reducing downside risk, but that how and to what extent differs between the countries. Within-household provided insurance reduces the countercyclicality in the skewness of earnings in Sweden, but evidence of within-household insurance is much weaker in United States and in Germany. Government provided insurance, in the form of unemployment insurance, welfare benefits, aid to low income households, and the like, plays a more important role in all three countries; the effectiveness is weakest in the United States, and strongest in Germany.

Related Literature

This chapter is primarily related to two streams of the literature: the investigation of the cyclical properties of income risk and the design and analysis of government policy over the business cycle.

The question of how idiosyncratic income risk varies over the business cycle is essentially empirical, yet its answers have been dominated by parametric choices as a way to overcome the data limitations. Storesletten et al. (2004) addressed those difficulties and proposed an identification strategy that allowed exploiting a longer time span compared to that available in the micro data. Similar to our results, they find that income risk increases in recessions. However, as discussed in the introduction, they find this risk to be driven by countercyclical variance. This chapter is closer to Guvenen et al. (2014), also briefly discussed above, both in our non-parametric methods and in the findings. We also find the increase in income risk to be driven by higher-order moments. Moreover, compared to the latter paper, we extend the empirical analysis to different samples, demographic groups, income measures, and countries. We, together with contemporaneous research discussed below, confirm that the increase in downside risk in recessions is a pervasive phenomenon.

Despite the importance of this empirical question for policy analysis in general, there are few applications to countries other than the US. A notable exception is Bayer and Juessen (2012), who extend the framework in Storesletten et al. (2004) and apply it to household data in Germany, the UK, and the US. Limiting their analysis to symmetric business-cycle risk of wages, they find mixed evidence for the cyclicality of the variance of shocks; namely that variance is procyclical in Germany, acyclical in the UK, and countercyclical in the US. They attribute this result to the differences in institutions between the three economies. In this chapter, we compare three economies with very different institutions, and after allowing for the possibility of asymmetric changes find that all three countries exhibit similar cyclical patterns in higher-order labor income risk. Closer to our work, Busch et al. (2016) analyze the cyclicality of labor income risk in Germany, explicitly allowing for time variation of the skewness. Extending the identification approach of Storesletten et al. (2004) to the third moment, they come to the same substantial conclusion as we do; namely, that variation of income risk over the business cycle is asymmetric. Finally, concentrating on Italy, Blass-Hoffmann and Malacrino (2016) analyze the dynamics of earnings changes with a focus on a decomposition into its employment time and wage components.

Our focus on higher-order moments, in addition to the recent empirical evidence, is motivated by a number of theoretical and quantitative papers that highlight the importance of these for household consumption behavior to be empirically plausible. In particular, Constantinides and Ghosh (2017) allow labor income shocks to exhibit procyclical skewness in an asset-pricing model. Their model is able to match the cross-sectional distribution of market returns, resolving several puzzles in the finance literature, including the equity premium and excess volatility puzzles. These results are in line with earlier theoretical results shown in Mankiw (1986).

This chapter is also related to the literature on economic stabilizers and cyclical government policy. Similar to our work, McKay and Reis (2014) focus on the stabilization power of taxes and transfers. Their model allows for different channels through which fiscal policy can interact with the business cycle. Our exercise is related to their *social insurance* channel; that is, how these policies alter the risks households are exposed to and their subsequent consumption response. In line with our results, they find that transfers and taxes help reduce the welfare costs of recessions. Bhandari et al. (2015) study the design of optimal policy—transfers, taxes, and government debt---in response to aggregate shocks in a model with incomplete markets and redistribution concerns. They calibrate the model to US data, capturing the asymmetric variation in the tails of the distribution of earnings shocks. They find that it is optimal for the government to increase all three instruments as a hedging device against aggregate shocks.

The remainder of this chapter is organized as follows. The next section discusses the data sources, and Section 4.3 describes the empirical approach. Section 4.4 presents the results for gross (before-government) individual earnings and examines how the patterns of cyclicality vary by gender, education, and type of employment. Section 4.5 expands the analysis to households and includes various types of government social insurance policies to examine their impact on the cyclicality of higher-order risk. Section 4.6 uses a structural life-cycle consumption-savings model with partial insurance to quantify the welfare benefits of governments' social insurance policies in the three countries under study. Section 4.7 concludes.

4.2 The Data

This section provides an overview of the data sets we use in our empirical analysis, the sample selection criteria, as well as the variables used in the subsequent empirical analyses. Given the diversity of our data sources, we relegate the details to Appendix B.1. Briefly, we employ four longitudinal data sets corresponding to three different countries: the Panel Study of Income Dynamics (PSID) for the United States, covering 1976 to

2010;[2] the Sample of Integrated Labour Market Biographies (SIAB)[3] and the German Socio-Economic Panel (SOEP) for Germany, covering 1976 to 2010 and 1984 to 2011, respectively; and the Longitudinal Individual Data Base (LINDA) for Sweden, covering 1979 to 2010. The PSID and the SOEP are survey-based data sets. The PSID has a yearly sample of approximately 2000 households in the core sample, which is representative of the U.S. population; the SOEP started with about 10,000 individuals (or 5,000 households) in 1984 and, after several refreshments, covers about 18,000 individuals (10,500 households) in 2011.[4]

The SIAB is based on administrative social security records and our initial sample covers on average 370,000 individuals per year. It excludes civil servants, students and self-employed, which make about 20% of the workforce. From the perspective of our analysis, the SIAB has two caveats: (i) income is top-coded at the limit of income subject to social security contributions, and (ii) individuals cannot be linked to each other, which prohibits identification of households. We deal with (i) by fitting a Pareto distribution to the upper tail of the wage distribution[5] and with (ii) by using data from SOEP for all household-level analyses. Throughout the analysis we focus on West Germany, which for simplicity we refer to as Germany. LINDA is compiled from administrative sources (the Income Register) and tracks a representative sample with approximately 300,000 individuals per year.

For each country, we consider three samples: two at the individual level–one for males and one for females–and one at the household level. The samples are constructed as revolving panels: for a given statistic computed based on the time difference between years t and $t+k$, the panel contains individuals who are aged 25 to 59 in periods t and $t+k$ ($k = 1$ or 5) and have yearly labor earnings above a minimum threshold in both years. This threshold is defined as the earnings level that corresponds to 520 hours of employment at half the legal minimum wage, which is about \$1885 US dollars for the United States in 2010.[6] To avoid possible outliers, we exclude the top 1% of earnings

[2]The PSID contains information since 1967. We choose our benchmark sample to start in 1976 due to the poor coverage of income transfers before the 1977 wave. We complement our results using a longer period whenever possible and pertinent.

[3]We use the factually anonymous scientific use file SIAB-R7510, which is a 2% draw from the Integrated Employment Biographies data of the Institute for Employment Research (IAB).

[4]These numbers refer to observations after cleaning but before sample selection. Only the representative SRC sample is considered in the PSID. The immigrant sample and high income sample of the SOEP are not used, because they cover only sub-periods.

[5]The imputation is done separately for each year by subgroups defined by age and gender. For workers with imputed wages, across years, we preserve the relative ranking within the age specific cross-sectional wage distribution. The procedure follows Daly et al. (2014): see Appendix B.1.3 for details.

[6]For the United States, we use the federal minimum wage. There is no official minimum wage in Sweden or Germany during this period. For Germany, we a take a minimum threshold of 3 Euros (in

observations in the PSID and SOEP, but not in LINDA (which is from administrative sources). For each individual, we record age, gender, education, and gross labor earnings. By gross earnings we mean a worker's compensation from his/her employer before any kind of government intervention in the form of taxes or transfers.

The household sample is constructed by imposing the same criteria on the household head and adding specific requirements at the household level. More specifically, a household is included in our sample if it has at least two adult members, one of them being the household head,[7] that satisfy the age criterion and household income that satisfies the income criteria. At the household level, we will analyze pre- and post government earnings and disposable income. Pre-government earnings defined as the sum of gross labor earnings earned by the adults in the household. Post-government earnings is constructed by adding taxes and transfers, and disposable income by in addition adding capital income.

Classifying Expansions and Recessions

For the United States, the classification of expansionary and recessionary episodes is based on the NBER peak and trough dates, with small timing variations. Given the time span covered by our sample, we classify the following years as recessions: 1980-1983, 1991-92, 2001-2002, and 2008-2010. The main difference compared to the NBER list is that we treat the 1980-1983 period as a single "double-dip" recession because of the short duration of the intervening expansion and the lack of recovery in the unemployment rate. Based on this classification, there are four expansions and four recessions during our sample period.

For both Germany and Sweden, we base the dating of expansions and recessions on data from the Economic Cycle Research Institute (ECRI), which applies the NBER methodology to OECD countries since 1948. The classification is consistent with various aggregate measures of the German and Swedish economies, respectively. In the time period covered by the panel data, recession periods for Germany (peak to trough) are from January 1980 to October 1982, January 1991 to April 1994, January 2001 to August 2003, and April 2008 to January 2009. Our sample period hence covers four recessions and four expansions. For Sweden, ECRI recession periods are from February 1980 to June 1983, June 1990 to July 1993, and April 2008 to March 2009. This leaves us with three recessions and three expansions during our sample period.

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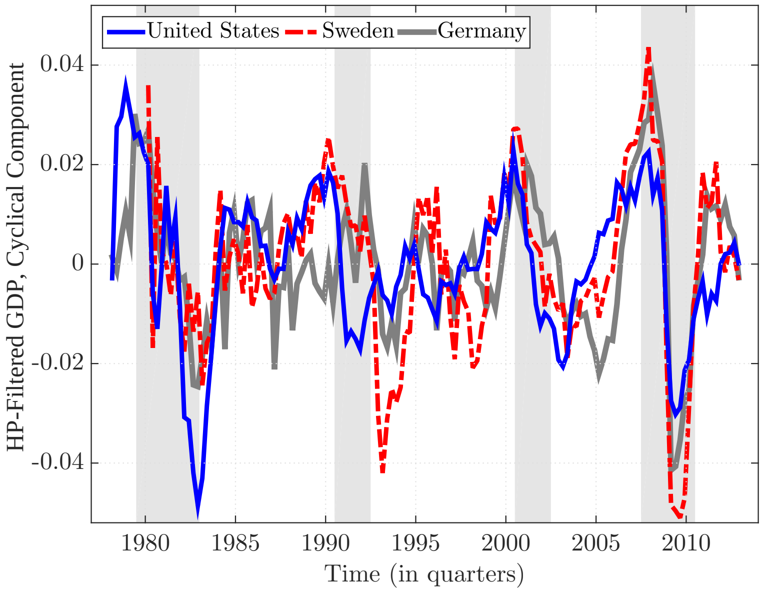
year 2000 Euros) for the hourly wage. For Sweden, the effective hourly minimum wage via labor market agreements was around SEK 75 in 2004 (Skedinger, 2007). For other years, we adjust the minimum wage by calculating the mean real earnings for each year, estimating a linear time trend for these means and removing that time trend from the SEK 75 minimum wage.

[7] In PSID and SOEP the head of a household is defined within the data set. In LINDA, the head of a household is defined as the sampled male.

Figure 4.1: Cyclical Component of Quarterly GPD Growth: United States, Germany, and Sweden



Note: The shaded areas in the figure indicate U.S. recessions according to our classification described in the text. The series for Germany corresponds to West Germany up to and including 1990Q4, and to (Unified) Germany from 1991Q1 on. The cyclical component is obtained by HP-filtering the series for GDP per capita from 1970Q1 to 2014Q1.

4.3 Empirical Approach

Measuring Income Volatility Over the Business Cycle

For each year, we calculate robust statistics of log s-year changes in income. We consider different choices of s in order to distinguish between earnings growth over short and long horizons, and interpret these as corresponding to "transitory" and "persistent" earnings shocks.

More specifically, we compute moments $m[\Delta_s y_t]$, where $y_t \equiv \ln Y_t$ (natural logarithm) and $\Delta_s y_t \equiv y_t - y_{t-s}$. The moments m we consider are: the log differential between the 90th and 10th percentiles (L9010), the (Kelley) skewness, and the top (L9050) and bottom (L5010) tails. For Germany and Sweden, s refers to 1- and 5-year changes. Due to the biennial structure of the PSID from the 1997 wave, our analyses of earnings for the United States refer to 2- and 4-year changes instead.[8]

We do not impose any parametric assumption on the dynamics of income but instead analyze the behavior of the tails of the distribution of earnings changes. We think this is important since interpretations when using the variance as a summary statistic of the

[8] We calculate overlapping s-year differences up to $\Delta_s y_{1996}$, and non-overlapping s-year differences from then and up to $\Delta_s y_{2010}$, for $s = 2, 4$.

distribution alone can be misleading. To see this point, consider a widening of both the upper and lower tails of a normally distributed variable. This is, P90 is shifted to the right and P10 is shifted to the left. This certainly implies an increase in the variance; the opposite, however, is not necessarily true. Think of the case in which only the lower tail shifts to the left. Notice how the overall dispersion of the distribution increases here as well, but if we were to interpret this increase in isolation we would wrongfully conclude that not only one tail, but both of them expand. Similarly, unchanged overall dispersion does not imply an unchanged distribution, but can be observed when both tails move together (i.e., one tail shrinks while the other expands). Both of these last two scenarios imply a change of the relative size of the tails–a feature summarized by the skewness of the distribution. In our empirical analysis, these are the two scenarios we observe when considering cyclicality: either overall dispersion does not change while skewness does, or dispersion is cyclical, caused by one tail expanding and the other shrinking.

We conclude that, when measuring income volatility, the tails should be explicitly analyzed. Furthermore, when relying on summary statistics of the distribution, limiting the analysis to the variance cannot possibly identify the nature of the change, yielding misleading results. Higher-order moments, like skewness, should be then considered. Note how any assumption on the distribution of income shocks would drive our results: a (log-) normal distribution cannot capture changes in skewness, for example. This is why, and in light of recent evidence on male earnings growth using administrative data for the United States (Guvenen et al., 2014), we take a skeptical–non parametric–point of view.

Broadening the Definition of Business Cycles

Some of the important macroeconomic variables do not perfectly synchronize with expansions and recessions, but their fluctuations might have an impact on earnings. For example, the U.S. stock market experienced a significant drop in 1987, during an expansion, and we can see in the time series analysis how the third moment falls sharply in that year. Similarly, the U.S. economy displayed an overall weakness in 1993-1994, which is evident in a range of economic variables, but these years are technically classified as part of an expansion by the NBER dating committee. Other examples are easy to find for Germany and Sweden (e.g., 1996). Therefore, the main focus of our analysis will be on the co-movement of higher-order moments of earnings changes with a continuous measure of business cycles. We use the (natural) log growth rate of GDP—i.e., $\Delta_s GDP_t \equiv \ln(GDP_t) - \ln(GDP_{t-s})$—as our measure of aggregate fluctuations. More specifically, we regress each moment m of the log income change between $t-s$ and t on a constant, a linear time trend, and the log growth rate of GDP between year $t-s$ and t :

Table 4.1: Short- and Long-Run GDP Growth Volatility: United States, Germany, and Sweden

		Std. Dev. of GDP Growth	
	Data period	short-run	long-run
United States	1976-2010	3.34%	4.44%
Germany	1976-2010	2.01%	3.95%
Sweden	1976-2010	2.36%	5.42%

Note: Short-run is 1-year difference for Germany and Sweden, and 2-year difference for the United States. Long-run is 5-year difference for Germany and Sweden and 4-year difference for the United States.

$$m\left(\Delta_s y_t\right) = \alpha + \gamma t + \beta^m \times \Delta_s(GDP_t) + u_t. \tag{4.1}$$

For a quantitative interpretation of the results reported in the next sections, Table 4.1 reports the short- and long-run volatility of GDP growth for each country and year sample considered along the chapter.

4.4 Empirical Results: Gross Individual Earnings

In this section, we address four questions concerning higher-order risk for individual earnings. First, we ask if the countercyclical skewness and the acyclical dispersion is a US-only phenomenon or a robust feature of business cycles that can be observed in other countries whose labor markets differ greatly from that in the U.S.. For example, according to OECD (1993) 15 percent of U.S workers are unionized and 21 percent are covered by trade union agreements. In Germany the equivalent shares are somewhat higher; 30 and 44 percent respectively, but in Sweden the overwhelming majority are members (84 percent) or are covered (94 percent) by trade union agreements. Second, we ask if business cycle variation in higher-order income risk differs across observationally distinct groups, defined by gender, education, private/public sector employment and occupation. Third, we ask if cyclicality of earnings changes can be attributed mainly to changes in wages or to changes in hours worked. Fourth, we ask if the countercyclicality of skewness and the acyclicality of dispersion found in U.S. administrative earnings data is also borne out in U.S. survey data, e.g., the PSID. This question is important because earlier papers that used the PSID and adopted parametric methods found strongly countercyclical variance of shocks. This begs the question: is it the data set or is it the methodology that accounts

Table 4.2: Cyclicality of Individual Earnings

	L9010	Kelley	L9050	L5010
	United States			
Males	–0.11	1.67***	0.57***	–0.68***
	(–0.51)	(5.00)	(3.71)	(–3.96)
Females	0.40***	0.62*	0.48**	–0.08
	(1.85)	(1.97)	(2.61)	(–0.52)
	Sweden			
Males	–0.11	3.74***	0.91***	–1.01***
	(–1.22)	(4.00)	(3.80)	(–3.74)
Females	0.43**	1.64***	0.67***	–0.24**
	(2.24)	(3.33)	(3.09)	(–2.67)
	Germany (SIAB)			
Males	0.15	5.48***	0.95***	–0.80***
	(0.36)	(5.80)	(3.14)	(–4.11)
Females	0.34	2.55**	0.80	–0.46*
	(0.48)	(2.05)	(1.25)	(–1.80)

Note: Each cell reports the coefficient on log GDP change of a regression of a moment of the distribution of changes in a income measure on log GDP change, a constant, and a linear time trend. Newey-West t-statistics are included in parentheses (maximum lag length considered: 3 for SIAB and LINDA, 2 for PSID). Asterisks ($*, **, * * *$) denote significance at the (10%, 5%, 1%)-level.

for these different conclusions?

Cyclicality of Dispersion

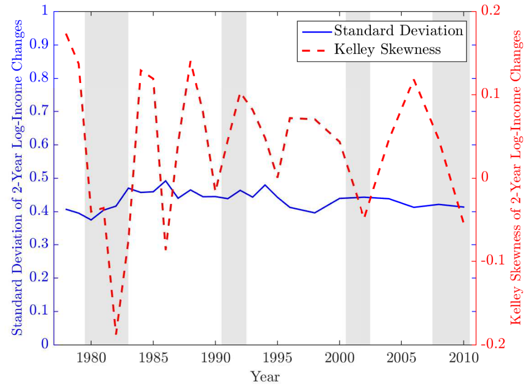
In Table 4.2, we report the cyclicality of four key statistics computed from the distribution of earnings changes of individual workers. To provide a comparative discussion, we report the results for all three countries in the same table. For now, we focus on the first row of each panel, corresponding to the sample of male workers in each country. The first column reports the cyclicality of the L9010. In the United States, the L9010 for males is acyclical, as seen from the small (–0.11) and statistically insignificant (*t-stat* of –0.51) coefficient. Turning to Sweden and Germany, the L9010 for male earnings are also acyclical.[9]

Overall, we conclude that in all three countries the dispersion of earnings changes does not display any robust pattern of cyclicality, judging from these regressions. In addition to being acyclical, the dispersion of earnings changes is quite flat over time (left panels of Figure 4.2). These figures should be compared with typical calibrations in the literature that assume the volatility of earning shocks doubles or triples during recessions. Here the

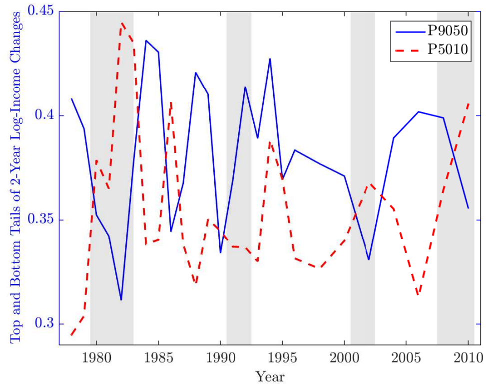
[9] All regression results based on SIAB data are robust to various robustness checks that address issues of top-coding and a structural break in the wage variable. See appendix B.3 for details.

Figure 4.2: Distribution of Short-Run Earnings Growth: United States, Sweden, and Germany (SIAB): Males

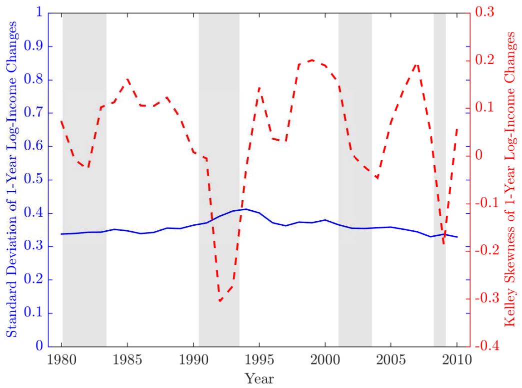
(a) United States, SD (left) and KS (right)



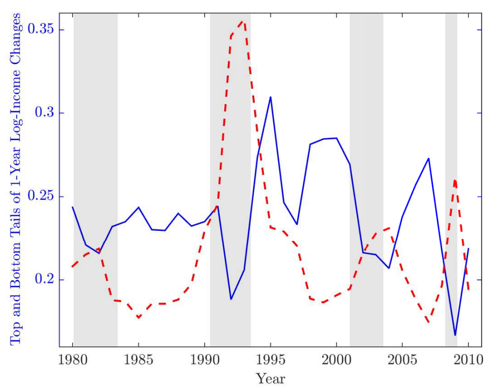
(b) United States, Upper and Lower Tail



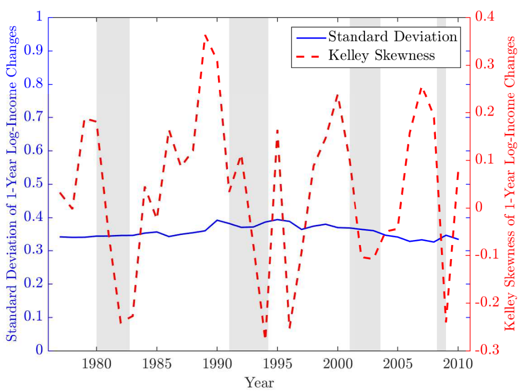
(c) Sweden, SD (left) and KS (right)



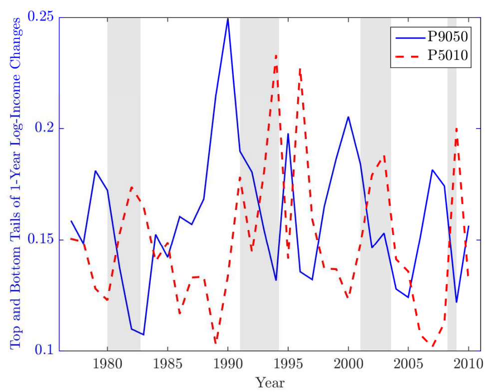
(d) Sweden, Upper and Lower Tail



(e) Germany, SD (left) and KS (right)



(f) Germany, Upper and Lower Tail



Note: Linear trend removed, centered at sample average.

largest movements are on the order of 10% to 15%, and they show no signs of cyclicality.

Cyclicality of Skewness

We next turn to the cyclical behavior of skewness. Column 2 reports a measure of asymmetry, called Kelley's skewness, defined as:

$$\mathcal{S}_k = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)}.$$

This measure has several attractive features compared with the third standardized moment. First, it is much less sensitive to extreme observations, since it does not depend on observations beyond the 90th and 10th percentiles of the distribution. This deals with the concern about potential outliers. It is therefore our preferred measure of skewness, especially when considering the U.S. and Germany (GSOEP) where measurement issues could be more important.[10] Second, the particular value of Kelley's skewness has a simple interpretation, in terms of the relative lengths of the top and bottom tails. In particular,

$$\frac{P90 - P50}{P90 - P10} = 0.5 + \frac{\mathcal{S}_k}{2}, \tag{4.2}$$

which can be used to compute the fraction of overall dispersion (P90-P10) that is accounted for by the top tail (P90-50) and consequently by the bottom tail (P50-P10).

Armed with these definitions, we turn to the left panels of Figure 4.2. In all three countries, Kelley's skewness is procyclical. This pattern is particularly striking in Sweden and Germany, where movements in Kelley's skewness are almost perfectly synchronized with the business cycle as defined by ECRI. The notable exception is the fall in Kelley's skewness in 1996, but note that the cyclical component of GDP did indeed fall in 1996 as displayed in Figure 4.1. Furthermore, Table 4.2 shows that the procyclicality of Kelley's skewness is (statistically) significant at the 1% level in all three countries. The coefficient is 1.67 for the U.S., 3.74 for Sweden, and 5.48 for Germany, showing more cyclicality when moving from the U.S. to Sweden and most for Germany. Thus, for example, if a typical recession in Sweden entails a drop in GDP growth of two standard deviations (from +1 to −1 sigmas, for a swing of $2 \times 0.0236 = 0.0472$), Kelley's skewness will fall by $0.0472 \times 3.74 = 0.177$. For the sake of discussion, suppose $\mathcal{S}_k^{\text{exp.}} = 0$ in an expansion, then $\mathcal{S}_k^{\text{rec.}} = -0.18$, which in turn implies from equation (4.2) that the upper tail to lower tail ratio, $(P90 - P50)/(P50 - P10)$ goes from 50/50 to 41/59 from an expansion to a recession. This is a large change in the relative size of each tail, especially for a country like Sweden, which might be thought of as displaying lower business cycle risk (due to the

[10] We have also analyzed the third standardized moment, and found very similar results.

high unionization rate, among others).[11]

Inspecting the Tails

At the expense of some oversimplification, it might be useful to think about a shift towards more negative skewness as arising from either a compression of the right tail or an expansion of the left tail or both. Thus, a follow-up question is: which one of these changes is driving the cyclical changes in skewness for each country? Again, the pattern is particularly striking in Sweden, see the middle right panel of 4.2. It shows that the top tail is procyclical, whereas the bottom tail is countercyclical. The last two columns of Table 4.2 shows that this pattern is present and (statistically) significant in all three countries. This means that, in a recession, the positive half of the shock distribution compresses relative to the median, whereas the negative half expands. Thus, the shift towards negative skewness happens through both tails moving in unison during recessions.

Furthermore, notice that for all three countries it turns out that the magnitude of movement of each tail is similar to each other. For example, for the U.S., the coefficient for L9050 is 0.57 and for L5010 is –0.68. The corresponding coefficients are 0.91 and –1.01 for Sweden, and 0.95 and –0.80 for Germany. Therefore, as log GDP growth fluctuates over the business cycle, the shrinking of one tail is matched closely by the expansion of the other tail, making the total dispersion, the L9010, move very little over the cycle. As a result, skewness becomes more negative in recessions without any significant change in the variance. This analysis shows that the behavior of higher-order risk is best understood by separately studying the top and bottom tails over the cycle, which can move together or independently. Focusing simply on a directionless moment, such as the L9010 or the variance, can miss important asymmetries that can matter for the nature of earnings risk. As we will see in a moment, whenever we observe cyclical dispersion, it is driven by *asymmetric* movements of the tails, and should not be thought of as a pure change in L9010 or the variance (which would imply an expansion/compression of *both* tails).

Survey vs. Administrative data

The earlier work on higher order income risk for male earnings (Guvenen et al., 2014), used administrative data from the U.S. Social Security Administration (SSA) records. As mentioned in the introduction, it lacks information on income components beyond earnings and one cannot link household members to each other. Similar restrictions apply to the administrative data we use for Germany (SIAB). This is why we use survey data (PSID for the U.S. and SOEP for Germany) to answer questions regarding insurance provided within households and by the government. These data sets however suffer from

[11] The corresponding changes in $\mathcal{S}_k$ for the U.S. and Germany are: 0.11 and 0.22 respectively.

having fairly few observations, which may imply that higher moments are imprecisely estimated. Reassuringly however, the results for individual earnings are very similar in PSID and SSA data, and in SIAB and SOEP data respectively. Specifically, we have re-run regression 4.1 using moments from the SSA data, as reported in Guvenen et al. (2014), and from SOEP data. The resulting coefficients for U.S. males using SSA data for each of the four moments are –0.07 , 2.31*** , 1.02*** , and –1.09**, respectively. These numbers are strikingly similar to those in the first row of the top panel in Table 4.2 The equivalent numbers using SOEP data are –1.33**, 1.76***, –0.21, and –1.12***. While these numbers differ somewhat from those in the first row of the bottom panel in Table 4.2, they tell the same story. In particular, male earnings changes in both SOEP and SIAB is characterized by asymmetric movements of the tails rather than uniform expansions and contractions of both tails.[12] The bottom tail is countercyclical in both data sets while the top tail is procyclical in SIAB but acyclical in SOEP. As a result, the L9010 is acyclical in SIAB and countercyclical in SOEP, but in both data sets skewness is procyclical.

4.4.1 Differences by Gender

We now turn to the cyclicality of higher-order risk for female workers and examine how they compare to the patterns for males. Focusing on the second row of each panel in Table 4.2, we see three main patterns. First, the L9010 of earnings changes is *procyclical* for U.S. and Swedish women but acyclical for German women. This is different from men, who displayed acyclical dispersion in all countries. Second, Kelley's measure of skewness is always procyclical–left-skewness is countercyclical–as indicated by the positive coefficient on log GDP growth, which is highly significant for Sweden (1% level), significant for Germany (5% level), and only slightly significant for the U.S. (10% level).

Third, inspecting the top and bottom tails separately (last two columns), we observe the expected pattern of cyclicality, whenever the coefficient is significant. In particular, L9050 is procyclical and significant for the U.S. and Sweden, whereas the L5010 is countercyclical and significant for Sweden and Germany.[13] Thus, just as for the case of male workers, the behavior of the variance is driven by an asymmetric movement of the two tails rather than a uniform expansion of both tails. In our view, this finding reiterates our earlier point that the L9010 or the variance are not ideal statistics to focus on when it

[12]We have also run 4.1 using the standard deviation of earnings changes as our measure for overall dispersion instead, and the coefficients are small (0.07 (SIAB), –0.12 (SOEP)) and insignificant (t-stat of 0.42 (SIAB), –054 (SOEP)) in both data sets.

[13]It is somewhat surprising that women in the U.S. seem to face less downside risk as measured by the L5010 differential compared with these two European countries.

comes to measuring higher-order earnings risk over the business cycle. Finally, it is worth noting that the magnitudes of the fluctuations in both Kelley's skewness and in the upper and lower tails separately are somewhat attenuated for women compared with men.

4.4.2 Differences Across Groups of Workers

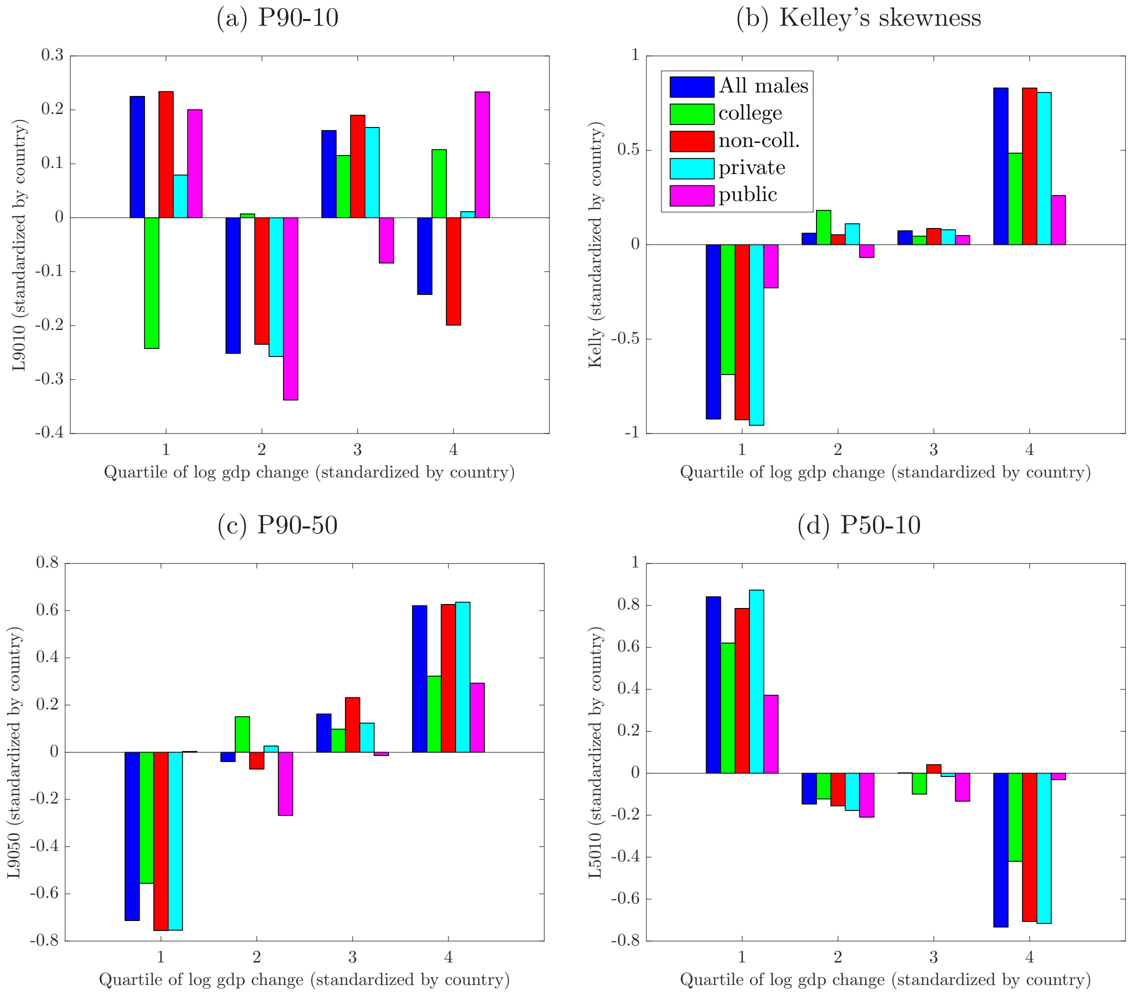
To shed light on the possible sources of cyclicality of higher-order income risk we now examine if it differs across observationally distinct groups. First we divide male and female workers into groups by education (college vs non-college graduates), or by private and public employment. These are two dimensions by which the three countries differ greatly. In Germany. 12 percent of men and 8 percent of women are college educated. In Sweden and the U.S. the equivalent numbers are 16 and 25 for males and 17 and 25 for females respectively. Differences in the size of public sector employment is even larger. Defining the public employment public administration, health care and education (sectors which in Germany and Sweden are dominated by public sector jobs or by jobs funded by the public),[14] the share of public sector employment in Sweden is more than twice as large as in Germany or the U.S.[15] Moreover, public sector jobs are often thought of as less risky, offering generous employment protection and less volatile compensation, so it is interesting to ask if this is borne out in the data.

For each of these groups we analyze higher order income risk by first computing average (standardized) moments across years and countries by quartiles of (standardized) log GDP change as shown in figures 4.3 and 4.4. The standardization of moments and log GDP change is performed independently for each country before pooling across countries, which implies that a deviation from zero indicates a standardized deviation from the country-specific mean of the moment. For each quartile the bars correspond to the average moment for (ordered from the left) the full sample (blue), college graduates (green), non-college graduates (red), private employment (cyan) and public employment (magenta), respectively. Figure 4.3 shows that earnings risk is very similar across all male subgroups; overall dispersion is acyclical (upper left panel), Kelley's skewness is procyclical (upper right panel), the top tail is procyclical and the bottom tail is countercyclical. Turning to females, Figure 4.4 shows a similar picture and, as noted above, that fluctuations in earnings risk is somewhat attenuated for women. For both males and females we see a

[14]Formally we define a worker as working in the public sector, if he/she works in these sectors in both years t and $t+k$ (where $k = 1, 5$). Historically most workers in these sectors were employed by the public; this is less true today.

[15]In Sweden about 23% of men and 63% of women work in the public sector (these figures have been relatively stable over the considered time period). In Germany a stable 10% of men work in the public sector, while the share of women steadily increased from about 23% to about 36% over the considered time period. In the U.S. 13 percent of males and 18 percent of females are employed in the public sector.

Figure 4.3: Average Moments by Quartiles of log GDP Change: Males



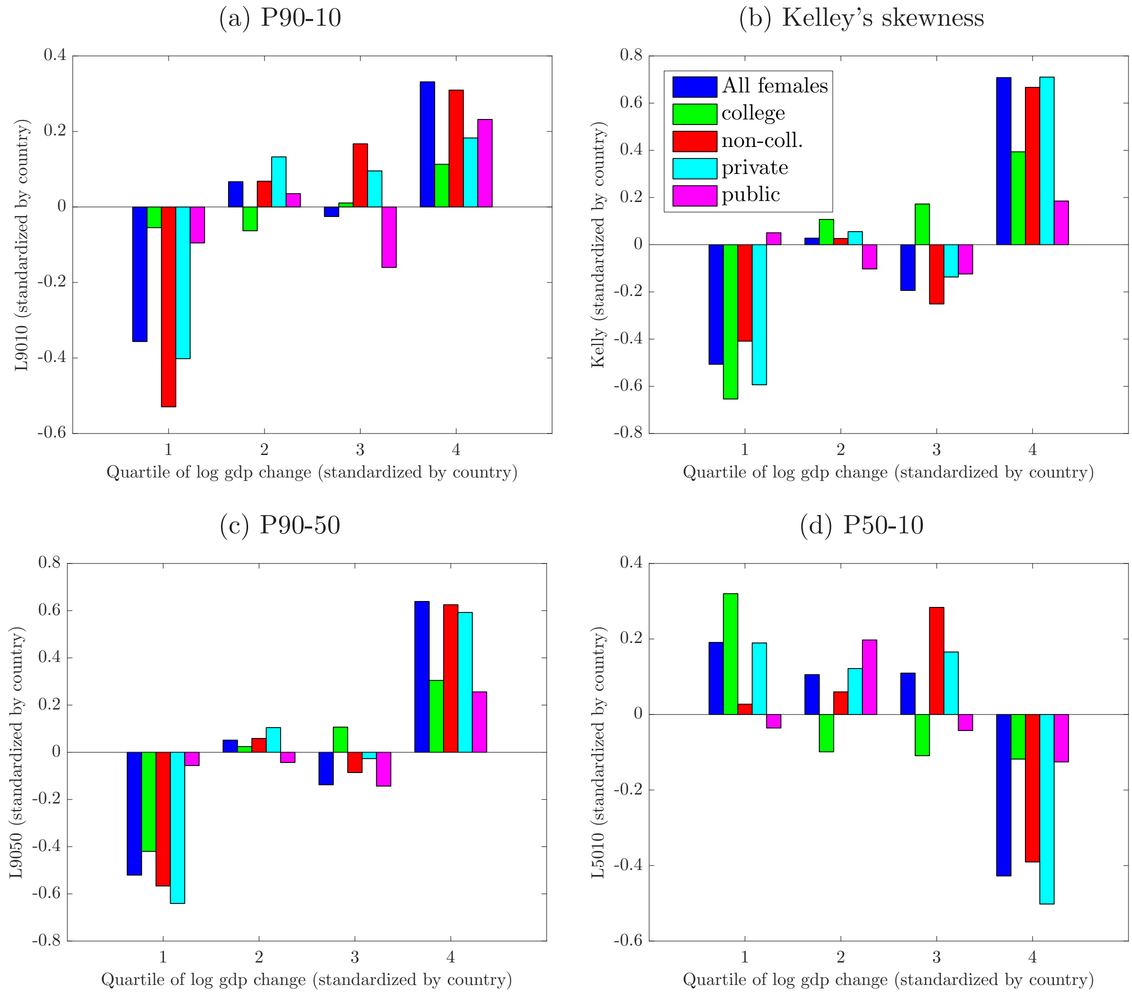
Note: For different samples, each bar shows the average moment across years and countries by quartiles of log GDP change. Both log GDP changes and moments are standardized by country.

strong asymmetric cyclical change of the distribution of earnings changes across groups.

For each group we have also computed correlations between the moments and log GDP change using equation 4.1 separately by country. These are displayed in Figure 4.5. Detailed results can be found in Appendix B.2. Each panel in the figure shows, starting from the left, the regression coefficients (from equation 4.1) with confidence intervals for males (solid) in the U.S.(blue), Sweden (red) and Germany (green), then followed by the equivalent regressions coefficients for females (dotted). Within each country-gender grouping, the regression coefficients are (ordered from the left) those from the full sample, college graduates, non-college graduates, private and public employment, respectively.

Figure 4.5 confirms the picture that emerged in Figures 4.3 and 4.4; higher order

Figure 4.4: Average Moments by Quartiles of log GDP Change: Females

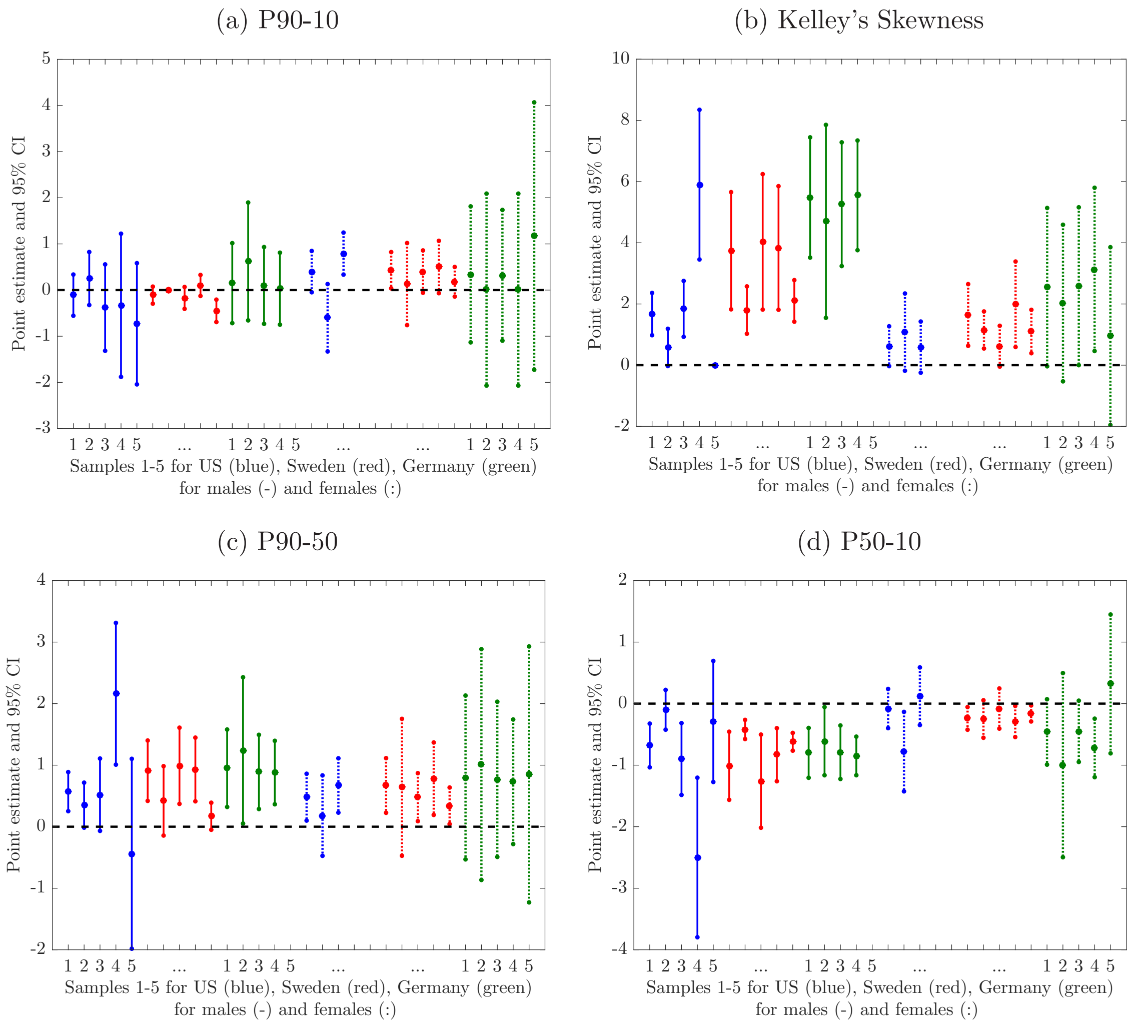


Note: See notes to figure 4.3.

earnings risk is similar across groups.[16] There are however some noteworthy differences. The magnitude of cyclicality is stronger for non-college graduates as compared to college graduates—particularly in the U.S. and Sweden, where it is about three times stronger. Moreover the magnitude of cyclicality for public sector workers is weaker in all countries. For example, in Sweden, the procyclicality of Kelley's measure of earnings is lower for the public sector (2.10*** for males and 1.10*** for females) compared with the private sector (3.83*** for males and 1.99*** for females). For males this is due to differences in the top tail; it compresses strongly for private sector employees, whereas it is acyclical in the public sector. The L5010 gap on the other hand fluctuates by comparable magnitudes for both groups. For women, the reduced cyclicality is due to both tails fluctuating less.

[16] Tables B.3 to B.6 in Appendix B.2 show the coefficients displayed in the figure.

Figure 4.5: Cyclicality of Individual Earnings and Wages: United States, Sweden, and Germany (SIAB)



Note: The samples are (1) Earnings: full sample , (2) Earnings: college graduates, (3) Earnings: non-college graduates, (4) Earnings: private sector, (5) Earnings: public sector. For details of samples see text. For the regressions, see note to table 4.2. Each • reports reports the coefficient on log GDP change.

Overall, it is somewhat surprising that, even for workers in the public sector in a country like Sweden with a reputation for high levels of public insurance, there is robust evidence of higher downside risk in recessions—compression of the top and expansion of the bottom—even if the magnitudes are somewhat smaller than in the private sector. This finding further strengthens the conclusion of this section that increasing downside earnings risk appears to be a robust feature of business cycles in developed countries, even with very different labor market institutions.

Differences Across Occupations

We now turn to occupations and explore the heterogeneity of cyclical earnings changes along this dimension. We are able to conduct this analysis for Germany; the SIAB provides time-consistent occupational codes based on the KldB-88, the 1988 version of the classification of occupations by the German Federal Employment Agency. We now run the cyclicality regressions separately for each occupation, where a worker contributes to the earnings changes of occupation j from t to $t+1$ if in year t he or she works in that occupation.

We first consider the highest level of disaggregation in the KldB-88, which defines five broad *occupational areas*; (1) farming, gardening, animal breeding, fishing, and similar occupations, (2) mining and mineral extraction, (3) manufacturing and fabrication, (4) technical occupations like engineering or laboratory work, and, (5) service occupations. For each occupation we have computed correlations between moments and log GDP change using equation 4.1. As seen in Table 4.3, the results are quite similar as compared with those for the full sample; in particular for male workers in manufacturing occupations, technical occupations, and service occupations.

We also consider a more disaggregated analysis and re-run the regressions for 30 *occupational segments*. While there is then more variation across occupations in terms of earnings cyclicality, the general pattern seen in the full sample of male and female remain; the lower tail is countercyclical for most occupational segments and the upper tail is mostly procyclical. Tables B.7 and B.8 in Appendix B.2 summarize the coefficients across the 30 occupational segments.

For both males and females the tail movements translate into the cyclicality procyclicality of Kelley's skewness in the by now familiar way.

Summing up, we find that broad occupational groups experience similar cyclicality with farming and mining related occupations being less cyclical. Regressions at finer level of disaggregation point towards interesting heterogeneity of earnings cyclicality across occupations.

4.4.3 Cyclicality of Earnings vs. Wages

A natural question that is raised by these results is whether the observed cyclicality of earnings changes can be attributed mainly to changes in wages or to increased risk of unemployment in economic downturns. The SIAB contains detailed information on the duration of each employment spell and on whether it is a part-time or full-time job. Focusing on full-time workers, we analyze the cyclicality of the distribution of wage changes and compare the results to the ones on earnings changes. We define a worker as

Table 4.3: Cyclicality of Earnings by occupational area; Germany (SIAB)

	L9010	Kelley	L9050	L5010
		Males		
Farming and related	4.56	5.64	3.80	0.76
	(1.23)	(1.51)	(1.52)	(0.45)
Mining, Mineral Extraction	2.62	3.23	1.32**	1.30
	(1.25)	(1.39)	(2.43)	(0.72)
Manufacturing, Fabrication	0.17	11.39***	2.00***	-1.83***
	(0.20)	(5.53)	(3.21)	(-3.99)
Technical Occupations	0.13	12.36***	1.51**	-1.38***
	(0.19)	(4.04)	(2.72)	(-3.64)
Service Occupations	0.59	8.89***	1.76**	-1.17***
	(0.68)	(3.92)	(2.41)	(-3.09)
		Females		
Farming and related	2.90	0.96	2.06	0.84
	(0.73)	(0.31)	(0.71)	(0.61)
Mining, Mineral Extraction	-5.59	12.26	1.61	-7.20**
	(-1.02)	(1.54)	(0.34)	(-2.59)
Manufacturing, Fabrication	-0.72	10.59***	2.48*	-3.20***
	(-0.48)	(4.95)	(2.00)	(-6.01)
Technical Occupations	-0.75	8.44**	1.41	-2.16***
	(-0.83)	(2.70)	(1.56)	(-2.82)
Service Occupations	0.85	4.09	1.45	-0.60
	(0.59)	(1.63)	(1.13)	(-1.15)

Note: See notes for Table 4.2.

full time if his or her full-time spells add up to at least 50 weeks of employment in a given year. (A less strict definition of full-time workers as 45 weeks of employment does not change the results.) The wage variable is the average daily wage rate, where the average is taken over all full-time spells. The same measure has also been used in Dustmann et al. (2009) or Card et al. (2013).[17]

In Table 4.4, rows 1 and 4 reproduce the results from Tables 4.2 for completeness. The first set of new results are in rows 2 and 5: these report the cyclicality regressions using average daily wages instead of annual earnings. The main finding for both males and females is that the cyclicality of wages for full-time workers are remarkably similar to

[17]In Germany, a full-time worker is entitled to an annual vacation time of 4 to 6 weeks, which is counted as part of the employment spell.

Table 4.4: Cyclicality of Individual Earnings vs. Wages; Germany (SIAB)

	L9010	Kelley	L9050	L5010
		Males		
Earnings	0.15	5.48***	0.95***	–0.80***
	(0.36)	(5.80)	(3.14)	(–4.11)
Full-Time Wages	–0.09	4.73***	0.30***	–0.39***
	(–0.54)	(6.31)	(3.77)	(–3.20)
Full-Time Wages	–0.12	4.98***	0.28***	–0.40***
(Firm Stayers)	(–0.81)	(5.78)	(3.29)	(–3.20)
		Females		
Earnings	0.34	2.55**	0.80	–0.46*
	(0.48)	(2.05)	(1.25)	(–1.80)
Full-Time Wages	0.03	2.12***	0.17**	–0.14
	(0.18)	(5.11)	(2.61)	(–1.58)
Full-Time Wages	0.02	2.28***	0.16***	–0.14
(Firm Stayers)	(0.13)	(4.84)	(3.17)	(–1.61)

Note: See notes for Table 4.2.

the cyclicality of earnings. Specifically, both measures of dispersion of wages are acyclical as was the case for earnings, and the point estimates for both skewness measures are very close for wages and earnings.[18] Naturally, the dispersion of earnings changes is wider than the distribution of wage changes, which is reflected by the point estimates on the tails (last two columns), which are about half as big for wage changes.

A question that remains is what happens to the wages of workers that stay at the same firm. We therefore further restrict the sample to those workers that work at least 50 weeks for the same employer in both year t and t+1.[19] The second set of new results is in rows 3 and 6: the cyclicality regressions for average daily wages for those workers who work at the same firm. The remarkable result is that even for those we observe the same qualitative pattern of cyclicality of wage changes. By and large, these results strongly indicate that the cyclicality results are driven by changes in wages even for full

[18] The sample of full-time female workers contains about 73% of women (who make for only 54% of the observations) that contribute to the measures of earnings change for women. The corresponding figures were 88% of individuals and 82% of observations for males. This implies that part-time employment plays a more important role for the female sample.

[19] The sample of full-time female workers that do not switch firms contains about 61% of women (who make for about 40% of the observations) that contribute to the measures of earnings change for women. The corresponding figures were 80% of individuals and 65% of observations for males.

time workers and not by hours.

4.5 Introducing Insurance

We now turn to various sources of insurance available in modern economies and gauge the extent to which they are able to mitigate such downside risk over the business cycle.

4.5.1 Within-Family Insurance

In the previous section, we have shown that higher-order moments drive individual earnings risk over the business cycle. While it is important to understand the underlying nature of labor income risk and the systematic differences across groups, most of our samples are composed by individuals in cohabitation.[20] Assuming pooling of resources within the household, the relevant income measure for many economic decisions is the joint labor income in the household, not individual income. We therefore shift our attention to joint labor earnings at the household level in order to shed light on the role of informal insurance mechanisms within the household. As mentioned earlier, it is not possible to link individuals in SIAB, so we rely on SOEP data instead.

Mixed Evidence of Within-Family Insurance

The first row of each panel in Table 4.5 displays the cyclicality of each moment of household earnings changes. In order to get a feeling for the decrease (or increase) of exposure to business cycle fluctuations, we compare these results to the corresponding measures for individual earnings from Table 4.2 and in particular male earnings as these on average constitute 71, 60, and 62 percent of household earnings in the United States, Sweden, and Germany, respectively. Additional evidence comes from the graphical analysis of the dispersion, skewness, and the tails, of male earnings changes and household earnings changes in Figures 4.6 and 4.7, respectively.

Considering cyclicality of dispersion, the patterns and magnitudes for household earnings line up with the ones described for individual male earnings for all countries: household earnings changes display no cyclicality of dispersion. This is true especially for Sweden and the United States. The countercyclical measure of dispersion (as measured by L9010) for Germany is driven by the lower tail and thus the overall pattern here mirrors the one of male earnings dispersion in SOEP (see Section 4.4).

The analysis of Kelley's skewness–and the inspection of the tails–yields very interesting results when comparing the three countries. In Sweden, intra-family insurance plays an important role in reducing downside risk over the business cycle: The estimated co-

[20]Only 12% of our benchmark individual sample in the United States lives in a singe-person household, for example.

Table 4.5: Cyclicality of Household Earnings

	L9010	Kelley	L9050	L5010
		United States		
Earnings	0.23	1.97***	0.93***	–0.71***
	(0.74)	(6.17)	(4.96)	(–3.20)
Post-Gov	0.59**	1.17***	0.72***	–0.14
	(2.44)	(3.13)	(3.42)	(–0.86)
Disposable	0.63*	1.13***	0.74***	–0.12
	(1.90)	(4.83)	(3.75)	(–0.65)
		Sweden		
Earnings	–0.02	2.24***	0.50***	–0.52*
	(–0.08)	(3.33)	(4.94)	(–2.00)
Post-Gov	–0.41*	0.94**	–0.03	–0.38**
	(–2.00)	(2.38)	(–0.44)	(–2.33)
Disposable	–0.43	1.50***	0.06	–0.49**
	(–1.64)	(3.89)	(0.61)	(–2.67)
		Germany (SOEP)		
Earnings	–1.31***	1.88**	–0.05	–1.26***
	(–3.60)	(2.68)	(–0.18)	(–4.26)
Post Gov	–0.18	0.66	0.07	–0.25
	(–1.09)	(0.85)	(0.32)	(–1.28)
Disposable	–0.16	0.56	0.05	–0.22
	(–1.11)	(0.67)	(0.21)	(–1.19)

Note: See notes for Table 4.2.

efficients on household earnings are smaller than those on male earnings and quite close to those on female earning. For example, the coefficient on Kelley's skewness is about 2.2 as compared to 3.7 and 1.6 on male and female earnings respectively. The difference is primarily driven by both tails reacting less than those for male earnings; the lower tail by about half and the upper tail by almost as much as compared to male earnings. Repeating the illustrative calculation from above, this would imply a move from an upper tail to lower tail ratio of 50/50 in a typical expansion to 45/55 in a recession—much smaller compared to the change to a ratio of 41/59 for male earnings and very similar to a ratio of 46/54 for females.

Evidence of within-family insurance is weaker for the United States and Germany. In both economies, the results suggest somewhat higher downside risk in recessions for household earnings that that for male earnings, and much higher risk than that for female earnings. Considering the tails separately for the two countries, the slightly stronger reaction of Kelley's skewness is primarily driven by larger movements in the upper tail in United States, whereas it is the lower tails that widens more in Germany.

In order to shed further light on the insurance within households, we consider the cyclicality of income for actual households in comparison to income changes for randomly formed couples. This way we want to see if there is anything special about households visible in the data, or if the dynamics of household income just represent the dynamics of male and female income. We therefore randomly pair heads and spouses for each t to t+1 change. For each random couple, we make sure that artificial income is above the lower income. The first set of results in each country panel of table 4.6 shows the bootstrapped mean, standard deviation and 10-90 confidence band of the regression coefficients. In both the US and Germany, we find the random couples to experience lower downside risk than actual households as measured by the cyclicality of L5010. For Sweden, the random couples' L5010 shows the same cyclicality as actual households. The next rows show the same results when not randomly pooling all heads and spouses, but controlling for some observables on the side of the head. When we control for age, we group heads into 7 age groups and in the pool of spouses for each age group are all spouses of heads in the actual data. Finally, we do the random coupling by age and education groups. As expected, the cyclicality experienced by random couples is more and more similar to actual households. Still, for the US and Germany we find actual households experiencing slightly higher cyclicality of earnings changes than their artificial counterparts. This suggests that the correlation between head's and spouse's labor market income is higher than for a random counterpart and uncontrolled characteristics play some role - like, e.g., most heads and spouses working in the same local labor markets.

We conclude that the responses of gross household earnings are heterogeneous across countries, with Sweden being the only economy where the family plays a clear insurance role against aggregate fluctuations. However, it is hard to extract further conclusions in disconnection to taxes and transfers payed and received by the household. In order to shed light on this issue, we move on to considering the role of social insurance policy over the business cycle.

4.5.2 Government and Social Insurance Policy

Focusing on the household as the relevant unit, we analyze the effectiveness of social policy in mitigating business cycle risk in addition to any insurance arrangements made within households. We evaluate the total insurance effect of the tax and transfer system by analyzing the cyclicality of post-government earnings as compared to household gross

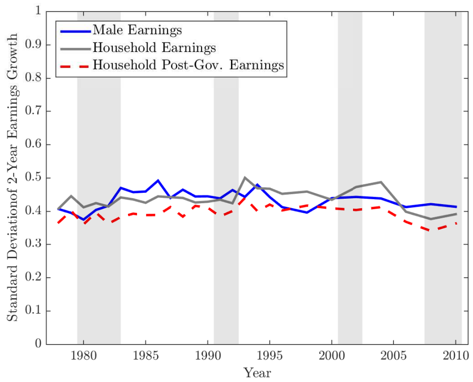
Table 4.6: Cyclicality of Earnings for Random Couples

	L9010	Kelley	L9050	L5010
	United States			
Actual Households	0.23	1.97***	0.93***	-0.71***
Random couples	0.21	1.27	0.63	-0.42
	(0.22)	(0.31)	(0.15)	(0.19)
	[-0.07 - 0.49]	[0.84 - 1.69]	[0.42 - 0.82]	[-0.66 - -0.19]
Random by age	0.03	1.51	0.65	-0.62
	(0.30)	(0.35)	(0.18)	(0.24)
	[-0.35 - 0.45]	[1.05 - 1.94]	[0.42 - 0.89]	[-0.92 - -0.33]
Random by age & educ.	0.01	1.49	0.63	-0.62
	(0.29)	(0.34)	(0.18)	(0.23)
	[-0.40 - 0.34]	[1.06 - 1.92]	[0.37 - 0.87]	[-0.92 - -0.32]
	Sweden			
Actual Households	-0.02	2.24***	0.50***	-0.52*
Random couples	-0.21	1.72	0.31	-0.52
	(0.03)	(0.05)	(0.02)	(0.02)
	[-0.25 - -0.16]	[1.66 - 1.79]	[0.28 - 0.33]	[-0.55 - -0.49]
Random by age	-0.20	1.76	0.32	-0.,53
	(0.03)	(0.06)	(0.02)	(0.02)
	[-0.25 - -0.16]	[1.68 - 1.85]	[0.30 - 0.35]	[-0.56 - -0.50]
Random by age & educ.	0.02	1.82	0.46	-0.43
	(0.03)	(0.06)	(0.02)	(0.02)
	[-0.02 - 0.06]	[1.72 - 1.89]	[0.43 - 0.48]	[-0.47 - -0.40]
	Germany (SOEP)			
Actual Households	-1.31***	1.88**	-0.05	-1.26***
Random couples	-0.99	1.28	-0.12	-0.87
	(0.29)	(0.48)	(0.18)	(0.22)
	[-1.35 - -0.62]	[0.64 - 1.88]	[-0.35 - 0.11]	[-1.14 - -0.58]
Random by age	-1.15	1.02	-0.25	-0.89
	(0.32)	(0.57)	(0.21)	(0.25)
	[-1.57 - -0.73]	[0.29 - 1.78]	[-0.53 - 0.01]	[-1.23 - -0.58]
Random by age & educ.	-1.19	1.01	-0.28	-0.91
	(0.33)	(0.56)	(0.21)	(0.25)
	[-1.65 - -0.80]	[0.25 - 1.70]	[-0.54 - -0.01]	[-1.24 - -0.60]

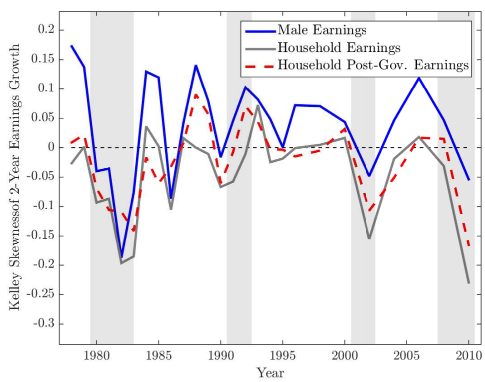
Note: See notes for Table 4.2. The parameter for the random couples is the mean over 250 bootstrap repetitions. In parentheses is the standard deviation, in brackets are the 10th and 90th percentiles. The regression for Sweden with education starts in 1991.

Figure 4.6: Standard Deviation and Skewness of Short-Run Earnings Growth: United States, Germany (SOEP), and Sweden

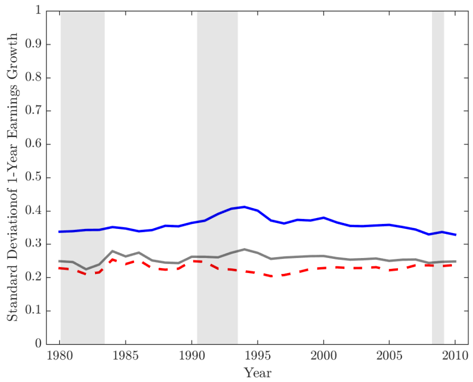
(a) United States, Std. Dev.



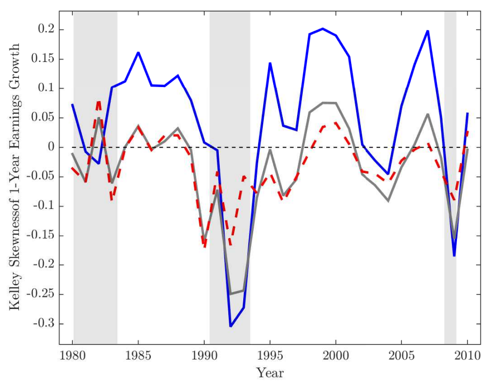
(b) United States, Kelley's Skewness



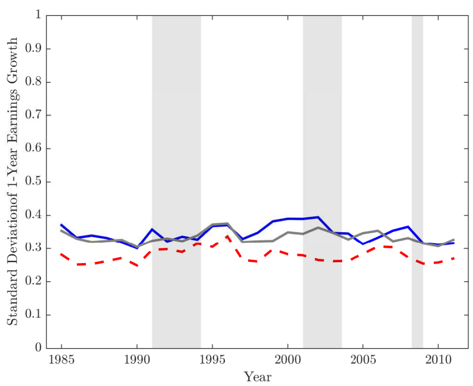
(c) Sweden, Std. Dev.



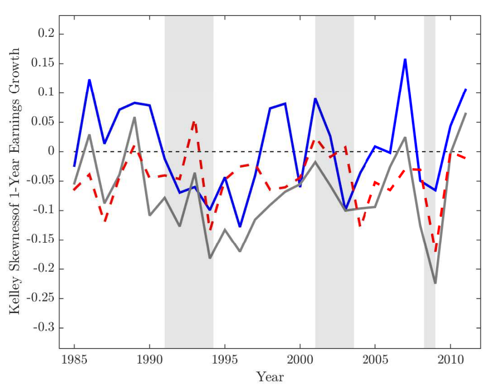
(d) Sweden, Kelley's Skewness



(e) Germany, Std. Dev.



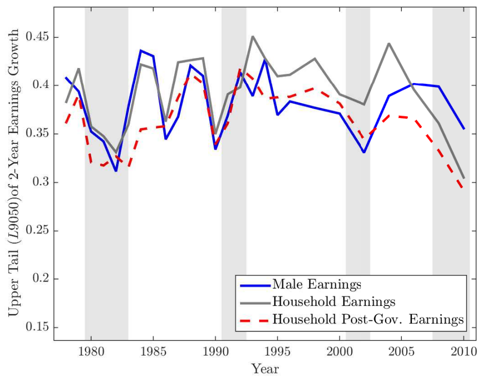
(f) Germany, Kelley's Skewness



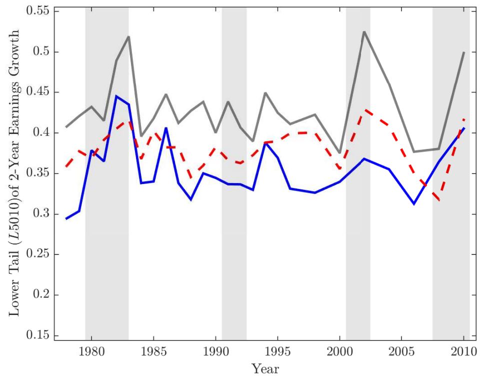
Note: Linear trend removed, centered at sample average.

Figure 4.7: Tails of Short-Run Earnings Growth: United States, Germany (SOEP), and Sweden

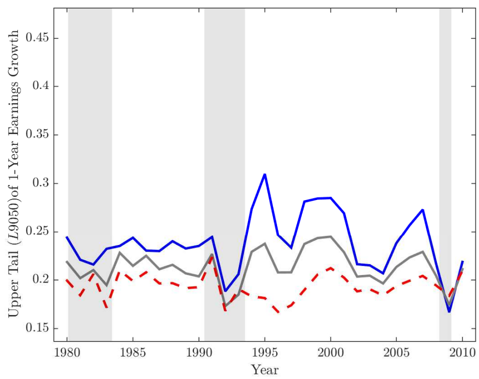
(a) United States, P90-50



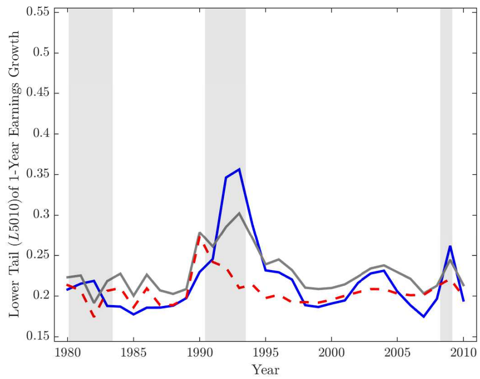
(b) United States, P50-10



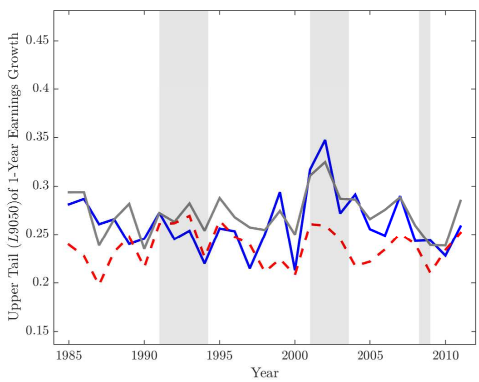
(c) Sweden, P90-50



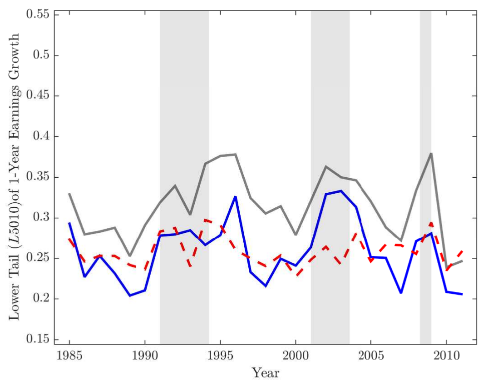
(d) Sweden, P50-10



(e) Germany, P90-50



(f) Germany, P50-10



Note: Linear trend removed, centered at sample average.

Table 4.7: Components of Social Policy

	LINDA	SOEP	PSID
1. Labor Market Transfers:	Unemployment benefits; Labor market programs	Unemployment benefits	Unemployment benefits; Workers' compensation
2. Aid to Low-Income Families:	Family support; Housing support; Cash transfers from the public; (no private transfers)	Subsistence allowance; Unemployment assistance (up to 2004); Unemployment benefits II (since 2005)	Supplemental Security Income; Aid to Families with Dependent Children (AFDC); Food Stamps; Other Welfare
3. Social Security and Pensions:	(Old Age) Pensions	Combined old-age, disability, civil service, and company pensions	Combined (Old Age) Social Security and Disability (OASI)

Note: Table lists the measures used in the three data sets to construct subcomponents of transfers.

earnings. In order to gain insights on the effectiveness of different policies, we then evaluate the relative importance of several subcomponents of transfers using the empirical tools employed in the previous analysis on income measures that in turn add certain transfers to household gross earnings.

For the analysis of subcomponents, we consider three main groups of transfers that are comparable across countries and for each country are consistently measured over time. The groups are (1) labor-market-related policies, (2) aid to low-income families, and (3) "pensions," and are listed in Table 4.7. Labor-market-related policies mainly consist of unemployment benefit payments—this component of social insurance policy is of particular importance for the mitigation of increased downside household earnings risk in recessions, if the nature of downside risk is (temporary) job loss of household head or spouse.

The second component considered, "aid to low-income families," consists of several measures of social insurance policies specifically aimed at at-risk households. The relevance of this type of transfer can therefore be expected to matter most for low-income households who have a higher likelihood of falling down to fulfilling 'at-risk' criteria in the course of a recession. The third component, pension payments, is not directly connected to business cycle considerations. It can still play a relevant role for household members near or at retirement age, who may take up pension payments instead of unemployment payments if they decide to leave the labor market upon job loss.

The Overall Effect of the Tax and Transfer System

We begin with a brief discussion on the overall effect of the government, comparing the cyclicality of pre- and post-government measures of household earnings listed in rows 1 and 2 of Table 4.5. Again, Figures 4.6 and 4.7 visualize the findings. We find that social policy is an important source of insurance against aggregate fluctuations in all three economies, with very similar overall effects. Motivated by the considerations from above sections, we directly consider the reactions of the upper and lower tails of income changes. In all three economies, downside risk is mitigated successfully by the tax and transfer system. In both the United States and Germany, the lower tail of post-government earnings changes is unresponsive to the business cycle–while significantly countercyclical for pre-government earnings. In Sweden, lower tail counter-cyclicality is dampened but still statistically significant (from a point estimate of –0.52 to –0.38).

Considering the cyclicality of the upper tail reveals differences between the countries. In Germany, it is unresponsive to the cycle for both pre-and post-government earnings. While both the U.S. and Sweden reveal procyclicality of L9050 of pre-government earnings changes, the L9050 of post-government earnings changes is acyclical in Sweden, but still procyclical in the United States. The different reactions of the tails translates into procyclical overall dispersion of post-government earnings changes in the U.S., and countercyclical dispersion in Sweden. Summarizing the reaction of overall dispersion and tails results in procyclicality of Kelley's skewness measure for both countries; though the procyclicality is much smaller for post- than for pre-government earnings.

To sum up, the analysis suggests that downside risk in recessions is mitigated by taxes and transfers. In Sweden, an additional effect are lowered upside chances in expansions. This lines up with considerations of Sweden as a country with a high degree of redistribution.

The Role of Subcomponents of Social Policy

The measure of post-government earnings used so far lumps a lot of very different transfers received and taxes paid by households. While this measure is appropriate for assessing the overall effect of the tax and transfers system, it is not as well suited for understanding the success of different social policies that specifically aim at mitigating downside risk or that aims at aiding low-income families, who can be expected to be especially vulnerable in recessionary periods. Therefore, we now consider different types of transfers separately. The results of the cyclicality analysis are listed in Table 4.8. As for for the estimates of total taxes and transfers, we compare the coefficients to the ones from the household gross earnings analysis in row 1 of Table 4.5. Recall that in order to be in the year t

base sample for the analysis, the lowest considered income measure of a household needs to be above the income threshold for that year. This way, we ensure that the sample is stable at the lower end of the distribution and results are not driven by low-income households entering the sample for a certain type of transfer but are not in the sample when considering another.

Table 4.8: Cyclicality of Household Earnings - Transfers Added Separately

	L9010	Kelley	L9050	L5010
	United States			
+ Labor transfers	0.60	1.59***	0.92***	–0.33
	(1.54)	(5.20)	(4.20)	(–1.34)
+ Aid to low-income	0.21	1.90***	0.89***	–0.69***
	(0.77)	(6.13)	(5.16)	(–3.33)
+ Pensions	0.22	1.82***	0.86***	–0.64***
	(0.80)	(5.61)	(4.79)	(–3.06)
	Sweden			
+ Labor transfers	–0.22	1.14***	0.13*	–0.35**
	(–1.23)	(4.23)	(2.04)	(–2.58)
+ Aid to low-income	–0.07	2.11***	0.42***	–0.49**
	(–0.38)	(3.72)	(4.51)	(–2.47)
+ Pensions	–0.07	2.34***	0.48***	–0.55**
	(–0.43)	(3.55)	(4.50)	(–2.68)
	Germany (SOEP)			
+ Labor transfers	–1.09***	1.34**	–0.13	–0.96***
	(–2.96)	(2.50)	(–0.60)	(–3.65)
+ Aid to low-income	–1.32***	1.66**	–0.11	–1.21***
	(–3.82)	(2.40)	(–0.47)	(–4.08)
+ Pensions	–1.21***	1.80***	–0.04	–1.17***
	(–3.30)	(3.10)	(–0.18)	(–4.58)

Note: See notes for Table 4.2.

The results in Table 4.8 show that out of the three transfer components, labor market related transfers (which have unemployment benefits as the main component) accounts for most of the reduction in downside. The other two components of transfers do not have any impact on cyclicality as measured by our cyclicality regressions. For all three economies, the point estimates when adding aid to low-income families or pensions are almost identical to the ones for gross earnings.

A closer look at the estimated coefficients reveal some interesting differences between the countries. In Sweden, labor market transfers account for almost the whole difference between pre- and post-government earnings cyclicality in the tails (compare rows 1 and 2 in Table 4.7 with row 1 in Table 4.8). Thus only a tiny amount is accounted for by the Swedish tax system or other transfers.

In the U.S., labor market transfers similarly accounts for the entire reduction in lower tail cyclicality. But the upper tail is unaffected by labor market transfer, and it is barely affected by aid to low-income families or pensions. This suggest that the lower procyclicality of the upper tail of U.S. post-government earnings changes is accounted for by U.S. tax system (or some interaction between taxes and transfers).

Finally, in Germany labor market transfers also mitigates downside risk, but it does so to a lesser extent than in Sweden and the United States. Rows 1 and 2 in Table 4.7 and row 1 in Table 4.8, shows that households earnings plus labor market transfers display significant down-side risk, (smaller but quite similar coefficients that those on household earnings), whereas post-government earnings changes are acyclical. The former finding is corroborated on individual earnings changes using our larger sample based on the SIAB data base. Besides individual earnings SIAB also contains information on unemployment benefits at the individual level. Table 4.9 shows results for individual level regressions for male and female earnings separately, when unemployment benefits are excluded (rows 1 and 3) and included (2 and 4). These individual level results line up well with the household level analysis conducted using SOEP data; labor market transfers mitigate the cyclicality of the tails but there is still significant higher order income risk even when unemployment benefits are included in the income measure. This suggest that the German tax system (or interaction terms between taxes and transfers) is the primary reason for post-government earnings being acyclical.

4.5.3 Sensitivity of Results to Choice of Lag Length

All results reported in the text refer to the distribution of what we label transitory, i.e., one-year changes of several income measures.[21] Given the focus of Storesletten et al. (2004) or Guvenen et al. (2014), to which we relate our results, on persistent income changes this choice needs to be discussed. The main reason for us to focus on one-year changes is that we choose a regression framework as our main tool of analysis. We make this choice, because we compare the cyclicality of income risk across countries. While for the US it is widely accepted to base the dating of business cycles on NBER recession dates,

[21] Recall that for the US we define two-year changes as transitory in order to account for the biannual nature of the PSID since 1997.

Table 4.9: Cyclicality of Individual Earnings Including Unemployment Benefits in Germany (SIAB)

	L9010	Kelley	L9050	L5010
Male Earnings	0.11	5.71***	0.97***	–0.86***
	(0.26)	(5.32)	(2.93)	(–4.40)
+Unempl. benefits	0.15	5.12***	0.84**	–0.70***
	(0.34)	(5.24)	(2.61)	(–4.01)
Female Earnings	0.46	2.69*	0.89	–0.44*
	(0.60)	(1.92)	(1.26)	(–1.74)
+ Unempl. benefits	0.50	2.43*	0.82	–0.32
	(0.67)	(1.82)	(1.22)	(–1.43)

Note: See notes for Table 4.2. Difference to estimates in 4.2 are due to the fact that regressions start in 1981 instead of 1976.

this dating is less clear cut for both Germany and Sweden. More generally, it is not clear that in a cross-country comparison the dating of business cycles is of the same quality in terms of capturing actual economic conditions. Our regression framework allows a very clear interpretation and comparison of cyclicality of income changes.

Moving to five-year changes—which are closer to capturing persistent changes—would imply problems with the regression analysis for two reasons. One option would be to use non-overlapping five-year changes of income and GDP, another would be to use overlapping changes. The first option would give too few data points for a regression analysis, while the second would open the door to usual problems of overlapping data.

The time-series of five-year changes is shown in figures B.1 to B.3 in Appendix B.4. Comparison to the one-year changes suggest the same qualitative patterns.

4.6 Welfare Analysis

In this section, we quantitatively address the question of how successful government policy is in insuring households against business cycle fluctuations of earnings risk. For that purpose, we estimate income processes for pre-government household labor income and, separately, for post-government household income. The process is specified flexibly as a mixture of normals with time-varying moments to allow for cyclical higher-order risk. Given estimated processes, we quantify the welfare gain of the existing tax and transfer system for the average household as the consumption equivalent variation (CEV) that is necessary to make households facing the pre-government income stream indifferent to facing the post-government income stream.

Our estimation is based on earnings data, so we use a model to simulate consumption profiles of households facing either pre- or post- government income streams. It is well documented that households are able to partially insure against income changes via various mechanisms (see, e.g., Blundell et al., 2008a). Reflecting this, we use a variant of the partial insurance model by Heathcote et al. (2014) to quantify the welfare gains. We do this exercise for all three countries. Before going to the results of the model-based welfare analysis in section 4.6.2, the next subsection discusses the estimation of the income process.

4.6.1 Estimation of Pre- and Post-Government Income

Let Y_t denote household earnings in period t, and define $y_t \equiv \log Y_t$. We assume y_t evolves according to the following process:

$$\begin{aligned} y_t &= z_t + \theta_t \\ z_t &= z_{t-1} + \zeta_t \end{aligned} \tag{4.3}$$

where ε_t is an *iid* transitory shock with distribution $\mathcal{N}(\mu_\theta, \sigma_\theta)$,[22] and ζ_t denotes a permanent shock with time-varying and business-cycle dependent distribution, modeled as in McKay (2016).

In particular, ζ_t follows a mixture of three normals $\mathcal{N}(\bar{\mu}_t + \mu_i - \phi_i x_t, \sigma_i)$, with respective probability p_i, $i = 1, 2, 3$, where $\sum_{i=1}^{3} p_i = 1$ and $x_t \equiv GDP$ growth. $\bar{\mu}_t$ is simply a normalization such that $\mathbb{E}(e^{\zeta}) = 1$. We use GDP growth as the empirical measure of aggregate fluctuations in order to make the quantitative results easily interpretable in relation to the empirical estimates shown in section 4.4. The parameter ϕ determines how much of aggregate risk is transmitted to idiosyncratic earnings risk and will be estimated alongside the other parameters that drive the distributions of the shocks.

We estimate $\theta = (\sigma_\theta, p_1, \mu_2, \mu_3, \sigma_1, \sigma_2, \phi)$[23] by Method of Simulated Moments (MSM). We target the time series of the 10th, 50th, and 90th percentiles of the 1, 3, and 5-year earnings changes distribution,[24] as well as the age profile of the cross-sectional variance from age 25 to 60. Tables B.13a and B.13b show the parameter estimates for the three economies under both scenarios. Appendix B.5 includes the comparison between the simulated moments at these parameters and the empirical moments, as well as further

[22] μ_θ is chosen such that $\mathbb{E}\left(e^{\theta}\right) = 1$.

[23] For identification purposes, we impose $\mu_2 \geq 0$, $\mu_3 \leq 0$, and $\phi_1 = 0$. With this assumption, the time-varying means of the three mixtures will control the center, right tail, and left tail of the distribution of ζ, respectively. For practical purposes, we further assume $p_2 = p_3, \sigma_2 = \sigma_3$.

[24] In the case of the United States, we target the 2, 4, and 6-year changes.

details on the simulation and estimation implementation.

4.6.2 Quantitative Model

The earnings changes we estimated reflect both actual ”shocks” in the sense of unforeseen income changes, as well as expected changes (Guvenen and Smith, 2014). Further, shocks differ in their nature, and some shocks are insurable, while others are not. Heathcote et al. (2014), HSV hereafter, set up a model populated by a continuum of islands, each of which in turn is populated by a continuum of agents. Two types of shocks exist in their economy, one common to all members of an island and the other individual specific. Island refers to a group of workers that are described by the same history of uninsurable shocks. Islands can be thought of as a network of family members, who perfectly share the risks faced by each individual. If, e.g., all family members work in the same industry and live in the same region, there will be shocks that hit every member equally and hence cannot be insured within the family network. Importantly for the model estimation, there is no need to define empirical counterparts to the model islands, and all parameters can be identified solely with aggregate moments. Given some assumptions on the market structure, outlined below, HSV show the existence of a non-trade equilibrium in the spirit of Constantinides and Duffie (1996). In this equilibrium, there is no asset trade across islands while agents within an island insure themselves perfectly against the individual-specific shocks. This reflects insurable (within island) and uninsurable (island level) shocks.

Model Structure

We employ a version of the HSV model, in which we abstract from endogenous labor supply. We also stay agnostic about the specific functional form of the tax and transfer system. Instead, we confront the model agents with the estimated pre-government earnings process and derive the implied consumption profile faced by expected utility maximizers, whose only choice (on top of engaging in asset trade) is consumption. We then consider the alternative world in which agents face the estimated post-government earnings process and derive their consumption profiles.

Specifically, household income is assumed to follow

$$y_t = \alpha_t + \varepsilon_t,$$

where α_t is the ”island-specific” component, that is common to a continuum of agents, which are additionally characterized by ”individual” component ε_t. This individual component in turn has a permanent part κ_t and a transitory part θ_t.

$$\begin{aligned}
\alpha_t &= \alpha_{t-1} + \omega_t \\
\varepsilon_t &= \kappa_t + \theta_t \\
\kappa_t &= \kappa_{t-1} + \eta_t \\
\theta_t &\sim F_{\theta,t} \\
\eta_t &\sim F_{\eta,t} \\
\omega_t &\sim F_{\omega,t}
\end{aligned} \tag{4.4}$$

Workers live finite lives. Each period a mass $(1-\delta)$ of newborns enters the economy with age 0. The probability of survival from age a to age $a+1$ is constant at δ. New-born agents maximize discounted life-time utility. For the per period utility function we use log utility: $u(c_t) = \log(c_t)$.

Age 0 agents entering in year b hold zero financial wealth and are allocated to an island of agents that then share the same sequence of uninsurable shocks $\{\omega_t\}_{t=b}^{\infty}$. There exists a full set of state-contingent claims for individual-specific shocks. Across islands, individuals can trade contracts contingent on their individual level shocks, while inter-island contracts are non-existent.

In equilibrium, log consumption and consumption change is given by:[25]

$$\log c_t(\mathbf{x}_t, \varepsilon_t) = \alpha_t + \log \int \exp(\varepsilon_t)\, dF^a_{\varepsilon,t}, \tag{4.5}$$

$$\Delta \log c_{t+1} = \omega_{t+1} + \left(\log \frac{\int \exp(\eta_{t+1})\, dF_{\eta,t+1} \int \exp(\theta_{t+1})\, dF_{\theta,t+1}}{\int \exp(\theta_t)\, dF_{\theta,t}} \right) \tag{4.6}$$

Note that the uninsurable shock ω_{t+1} that realizes for an individual translates one for one to consumption. The individual realizations of the two insurable shocks, however, do not at all affect consumption: given perfect risk sharing, all members of an island consume the mean realization of these shocks.

Distribution of Shocks

In order to use the model, we need to translate the estimated earnings process (4.3) into the process specified in (4.4). In the estimation the transitory component is assumed to be drawn from a Gaussian distribution, which directly translates into the distribution θ_t from (4.4). Permanent earnings changes are drawn from a mixture of three normal

[25] The derivation of consumption outlined in HSV carries over 1:1 to our simplified version of their model, which abstracts from the tax function and endogenous labor supply

distributions. In specification (4.4), the overall permanent earnings change is given by $(\omega_t + \eta_t)$, the insurable (individual-level) and the uninsurable (island-level) part. We now assume that both types of permanent shocks are drawn from time-varying mixture distributions. We scale the estimated parameters of the permanent shocks such that the variance of η_t (ω_t) is equal to the fraction λ (1-λ) of the overall variance of the permanent shock ζ:

$$\eta_t \sim \begin{cases} \mathcal{N}(\lambda^{1/2}\mu_{1,t}, \lambda\sigma_1^2) & \text{with probability } p_1 \\ \mathcal{N}(\lambda^{1/2}\mu_{2,t}, \lambda\sigma_2^2) & \text{with probability } p_2 \\ \mathcal{N}(\lambda^{1/2}\mu_{3,t}, \lambda\sigma_3^2) & \text{with probability } p_3 \end{cases} \tag{4.7}$$

$$\omega_t \sim \begin{cases} \mathcal{N}((1-\lambda)^{1/2}\,\mu_{1,t}, (1-\lambda)\,\sigma_1^2) & \text{with probability } p_1 \\ \mathcal{N}((1-\lambda)^{1/2}\,\mu_{2,t}, (1-\lambda)_2^2) & \text{with probability } p_2 \\ \mathcal{N}((1-\lambda)^{1/2}\,\mu_{3,t}, (1-\lambda)\,\sigma_3^2) & \text{with probability } p_3 \end{cases} \tag{4.8}$$

This scaling implies that the first three moments of η_t and ω_t are given by $E[\eta_t] = \lambda^{1/2}E[\zeta_t]$, $var[\eta_t] = \lambda var[\zeta_t]$, and $skew[\eta_t] = skew[\zeta_t]$ (for ω replace λ with $1-\lambda$); see Appendix B.6.[26]

In this setup, λ is the measure of the degree of partial insurance against permanent shocks: it simply measures the share of the total permanent variance that is accounted for by the insurable component. In line with the estimation we draw changes to x_t from a Standard Normal distribution and for each t calculate the parameters of the transitory and permanent shock components. In order to break the permanent shocks into an insurable and an uninsurable component we exogenously pick a value for λ and then simulate income and consumption profiles for a number of model agents.

Household i's lifetime utility when facing the pre- or post-government income streams is given by:

$$U_i^j\left(\left\{c_{ia}^j\right\}_a\right) = \sum_a (\beta\delta)^{a-1}\, u\left(c_{i,a}^j\right),$$

for $j = pre, post$, and $c_{i,a}^j$ is consumption of household i at age a when facing income stream j.

Utilitarian welfare in the world of the pre-government income stream when agents receive per-period consumption equivalent variation CEV is given by $W^{pre}(CEV) \equiv \sum_i U_i^{pre}\left(\left\{(1+CEV)\,c_{i,a}^{pre}\right\}_a\right)$, similarly utilitarian welfare in the post-government world is $W^{post} \equiv \sum_i U_i^{post}\left(\left\{c_{i,a}^{post}\right\}_a\right)$. We search for the CEV that ensures $W^{pre}(CEV) = W^{post}$, which with homogeneity of the per-period utility function can be calculated in

[26] We then shift the η and ω shocks by d_η and $d_\omega$such that $E[exp(\eta + d_\eta)] = E[exp(\omega + d_\omega)] = 1$.

closed-form and for log utility is

$$CEV = \exp\left(\frac{W^{post} - W^{pre}}{N}\frac{1-\beta\delta}{1-(\beta\delta)^{A}}\right) - 1, \tag{4.9}$$

where N is the number of individuals and A is the maximum age.

We evaluate the welfare gains for several values of the degree of partial insuranceλ. For the remaining model parameters we follow HSV, i.e., we set the annual survival probability to $\delta = 0.996$, the preference discount factor to $\beta = 0.95$. We simulate the model economy for 10 cohorts, each consisting of 10,000 individuals that live for a maximum of 100 years and calculate their expected present value utility at model age 1. Each cohort lives through a different macroeconomic history of log GDP changes, which we draw independently from a Normal distribution. The initial distribution of earnings at model age 1 is drawn from a lognormal distribution that resembles the overall dispersion at age 25 from the data. To be precise, we assume that earnings at age 25 are composed by the sum of a transitory component and two permanent components. We draw the transitory component from a lognormal distribution with variance of transitory shocks and then draw the uninsurable and insurable parts of the permanent shocks from lognormal distributions with λ and $(1 - \lambda)$ times the remaining variance. Thus, total variance at model age 1 corresponds to data variance at age 25. Then, agents accumulate shocks as described above. Using (4.9), we calculate the CEV for each cohort and then take the average over cohorts to calculate the welfare gains which are shown in table 4.10.

The degree of partial insurance λ is set to be the same in the two alternative worlds, i.e., pre- or post-government income. This reflects that we explicitly do not want to capture any partial insurance by the tax and transfer system. As expected, a higher value of partial insurance implies a lower gain from introducing the tax and transfer system: households are insured better against shocks and so the individual realization of earnings changes is less relevant for actual consumption. If the channels of partial insurance available to households beyond taxes and transfers reduce earnings volatility by 50 percent, the introduction of the tax and transfer system amounts to a welfare gain of about 7.4% of annual consumption for the average American household facing the pre-government income stream. These numbers are 9.8% and 6.2% for Sweden and Germany, respectively. A higher degree of partial insurance implies less scope for the tax and transfer system to insure households against income fluctuations.

Summarizing, in all three economies, the welfare gains resulting from the tax and transfer system are large and of similar magnitude. The Swedish tax and transfer system is estimated to yield a higher welfare gain than its German and American counterparts.

However, comparing the US to Germany, it is surprising that our results point towards slightly higher gains in the United States.

Table 4.10: Welfare Gains of the Tax and Transfer System

	$\lambda = 0.75$	$\lambda = 0.5$
United States	3.6	7.4
Sweden	4.7	9.8
Germany	3.1	6.2

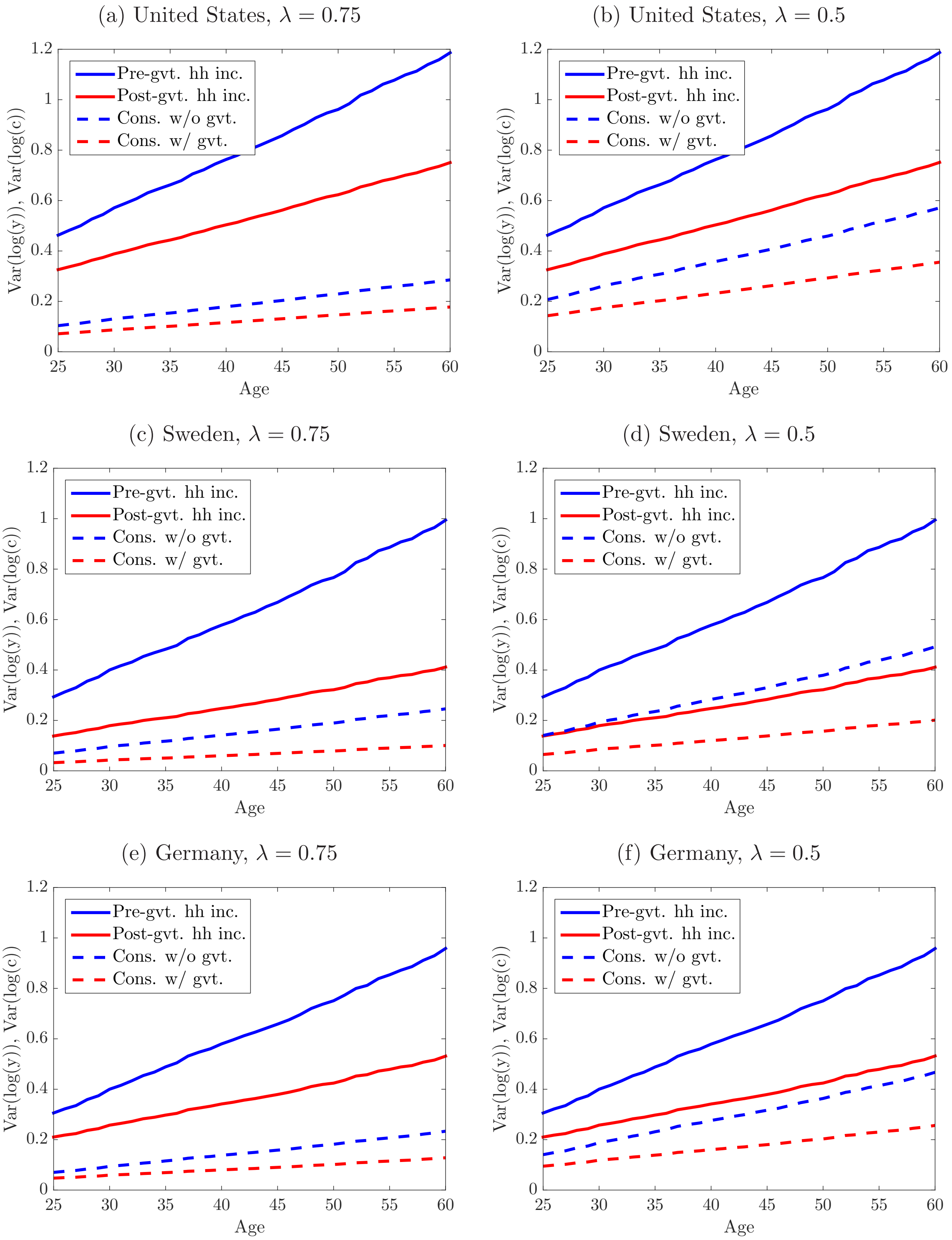
Note: λ denotes the degree of partial insurance against permanent shocks; the per-period utility function is $\log(c)$. The table entries show the consumption equivalent variation in percentages that is necessary to make households indifferent between the (compensated) pre-government income stream and the post-government income stream.

Digging deeper into the structure of the model economy, table 4.11 summarizes moments of the distributions of (log) income changes and of (log) consumption changes in expansions and contractions. The clear pattern that emerges across countries in the simulations is that the consumption stream is less volatile, and that the distribution of both income and consumption changes changes asymmetrically with aggregate conditions, in the sense that the distribution is more skewed to the right in expansions. Zooming in on the simulated income and consumption profiles, figure 4.8 shows the variances over the life cycle. The variance of the pre-government income stream is higher and rises faster that for the post-government income stream, which translates to similar behavior of the consumption inequality over the life cycle.

The described welfare analysis is based on an imposed structure with strong assumptions. We complement these results with a more reduced form estimate of the welfare gains. Consider Table 4.12: it shows moments of the distribution of income changes coming from pooled samples for each country for the income measures considered throughout the analysis in the preceding sections. Let us focus on the moments of pre- and post-government household income. In all three countries, the tax and transfer system overall closes the distribution of earnings changes: both upper and lower tails are smaller. Also a finding common to all economies is that the lower tail is affected more than the upper tail, which is reflected by a less negatively skewed distribution. For example, in Sweden the distribution of post-government earnings changes is even symmetric on average. For the United States, the described pattern is very weak: Kelley's skewness is only slightly affected and the measure based on central moments is unchanged to the second digit.

Not only is the overall dispersion smaller, and the distribution more symmetric, when

Figure 4.8: Variance of the Simulated Life Cycle Profiles of Income and Consumption: United States, Germany, and Sweden



Note: Figures show life cycle variance profiles in the simulated model. For details see text.

Table 4.11: Moments of Income and Consumption Changes in the Model Economy

	L9010	Kelley	L9050	L5010
	United States			
HH Earnings	0.84	0.02	0.43	0.41
	0.83	–0.01	0.41	0.42
HH Post Gov	0.75	0.01	0.38	0.37
	0.74	–0.00	0.37	0.37
Consumption w/o GOV	0.15	0.03	0.08	0.07
	0.14	–0.02	0.07	0.07
Consumption w/ GOV	0.12	0.03	0.06	0.06
	0.12	–0.01	0.06	0.06
	Sweden			
HH Earnings	0.48	0.06	0.26	0.23
	0.47	–0.04	0.23	0.24
HH Post Gov	0.38	0.07	0.21	0.17
	0.36	–0.04	0.17	0.18
Consumption w/o GOV	0.12	0.05	0.06	0.06
	0.12	–0.04	0.06	0.06
Consumption w/ GOV	0.07	0.08	0.04	0.03
	0.06	–0.06	0.03	0.03
	Germany			
HH Earnings	0.61	0.02	0.31	0.30
	0.65	–0.07	0.30	0.35
HH Post Gov	0.55	0.02	0.28	0.26
	0.56	–0.04	0.27	0.29
Consumption w/o GOV	0.11	0.02	0.06	0.05
	0.11	–0.08	0.05	0.06
Consumption w/ GOV	0.08	0.07	0.04	0.04
	0.08	–0.11	0.03	0.04

Note: The degree of partial insurance against permanent shocks, λ, is set to 0.75. The first line of each case denotes the average value of the moment in expansions; the second line denotes the average value of the moment in contractions.

comparing post-government household income to household gross earnings, also the share of households for which the annual income movements are very small is higher. This is what the higher kurtosis of post-government income suggests. Again, the effect is weakest for the United States and most pronounced for Sweden. Note that, in all three countries, the distribution of both pre- and post-government income changes is far away from a

Table 4.12: Moments of Income Changes

	Std.Dev	L9010	Skew	Kelley	Kurt	L9050	L5010	Nobs
	United States (PSID)							
Male Earnings	0.44	0.75	–0.42	0.03	13.69	0.39	0.36	42,698
HH Earnings	0.45	0.83	–0.24	–0.04	10.86	0.40	0.43	38,314
HH Post Gov	0.41	0.76	–0.24	–0.03	12.26	0.37	0.39	38,602
HH Disposable	0.39	0.79	–0.19	–0.02	10.50	0.39	0.40	38,632
+ Labor transfers	0.44	0.81	–0.24	–0.04	11.33	0.39	0.42	38,327
+ Aid to low–income	0.45	0.83	–0.25	–0.04	10.98	0.40	0.43	38,326
+ Pensions	0.45	0.83	–0.22	–0.04	10.85	0.40	0.43	38,354
	Sweden (LINDA)							
Male Earnings	0.36	0.45	–0.27	0.04	13.57	0.23	0.22	1,907,421
HH Earnings	0.26	0.45	–0.47	–0.04	14.22	0.21	0.23	1,113,760
HH Post Gov	0.21	0.35	–0.04	0.00	23.03	0.17	0.17	1,113,759
HH Disposable	0.20	0.35	0.03	0.01	17.64	0.18	0.17	1,113,759
+ Labor transfers	0.23	0.40	–0.44	–0.04	16.37	0.19	0.21	1,077,255
+ Aid to low–income	0.28	0.45	–0.34	–0.04	17.54	0.22	0.24	1,077,255
+ Pensions	0.25	0.44	–0.21	–0.01	15.00	0.21	0.22	1,077,255
	Germany (SOEP)							
Male Earnings	0.35	0.52	–0.23	0.00	15.89	0.26	0.26	64,572
HH Earnings	0.33	0.58	–0.78	–0.08	13.32	0.27	0.31	59,161
HH Post Gov	0.28	0.50	–0.11	–0.04	16.09	0.24	0.26	58,725
HH Disposable	0.27	0.50	–0.11	–0.03	14.99	0.24	0.26	58,853
+ Labor transfers	0.32	0.57	–0.70	–0.07	13.93	0.26	0.30	59,173
+ Aid to low–income	0.33	0.58	–0.83	–0.08	13.29	0.27	0.31	59,199
+ Pensions	0.32	0.57	–0.66	–0.06	13.55	0.27	0.30	59,166

Note: For Germany and Sweden, all moments refer to 1-year income differences, i.e. $s = 1$. For the United States, the reference sample is 1976-2010, with $s = 2$. Moments for $s = 1$ are reported in the appendix for the sample 1969-1996.

lognormal distribution (which has a kurtosis of 3).

4.7 Conclusion

This chapter studies how higher-order income risk varies over the business cycle, as well as the extent to which such risks can be smoothed within households or with government social insurance policies. To provide a broad perspective on these questions, we study panel data on individuals and households from the United States, Germany, and Sweden, covering more than three decades of data for each country. We find that the underlying variation in higher-order risk is remarkably similar across these countries that differ in many details of their labor markets. In particular, in all three countries, the variance of earnings shocks is almost entirely constant over the business cycle, whereas the skewness of these shocks becomes much more negative in recessions. Government provided insurance, in the form of unemployment insurance, welfare benefits, aid to low income households, and the like, plays an important role for reducing downside risk in all three countries; the effectiveness is weakest in the United States, and most pronounced in Germany. For Sweden we find that insurance provided within households plays a similar role.

Chapter 5

Labor Market Transitions in a Sectoral Business Cycle Model

5.1 Introduction

In this chapter, I present a structural real business cycle model with two sectors and involuntary unemployment. The goal of the model is to quantify the welfare costs of aggregate fluctuations in the presence of imperfect labor mobility across sectors. A specific feature of the model is that aggregate shocks have asymmetric implications across sectors. This incentivizes workers to switch sectors–which is costly. These costs can generate costs of aggregate fluctuations, which exceed those in a frictionless economy.[1]

Firms in the two sectors produce consumption goods with the same aggregate technology, in which labor is the only production factor. Workers have preferences that are non-homothetic in the two consumption goods, which implies that a shock wich affects income changes the optimal demand shares of the two goods. As a consequence, an aggregate productivity shock is propagated asymmetrically to the two sectors via the consumption response, which in turn changes the relative labor demand. Because workers cannot freely move to the sector with the higher labor demand, wages respond asymmetrically.

The structure of the model economy is in the spirit of Lucas and Prescott (1974) in the sense that it features separate sectors, or "islands", in which production takes place. More recent examples of Lucas and Prescott (1974) inspired models in the context of worker movements across sectors are Rogerson (2005) or Pilossoph (2014). Those and related studies have in common that mobility across sectors is induced by asymmetric sector-specific productivity shocks.

[1]The model evolved after many conversations with Peter Funk. I also thank Helge Braun for many helpful discussions.

Whether reallocation of workers across sectors is driven by sector-specific shocks, however, is an open debate. Lilien (1982) provides an argument in favor of sector-specific shocks that rests on the observation that the observed dispersion in employment growth rates correlates positively with aggregate unemployment. Abraham and Katz (1986) questioned this conclusion and discuss that also aggregate shocks can lead to the same correlation if the sectors differ in their long-term employment trends or the cyclical reaction of employment. In a recent paper along those lines, Garin et al. (2011) develop a framework with both aggregate and sector-specific shocks and discuss that over time aggregate shocks became less important relative to sectoral shocks.[2]

The novelty of the model in this chapter is that it generates asymmetric changes across sectors from an aggregate shock. The model therefore lends itself naturally to an analysis of the welfare costs of aggregate fluctuations. In an influential study, Lucas (1987) argues that the costs of aggregate fluctuations are small–and thus the potential gain of any stabilizing policy is small. He draws this conclusion from a back-of-the-envelope calculation of the fraction of per-period consumption individuals need to get in order to be indifferent to a world without any fluctuations. The calculation is based on several strong assumptions, one very important being full insurance against idiosyncratic risk. Motivated by the fact that this conclusion strongly contradicts general perceptions of economic fluctuations, a literature challenging Lucas' analysis evolved (comprehensive surveys can be found in Barlevy, 2005, or Lucas, 2003). A general conclusion of the literature is that workers' incomes vary over the business cycle in an asymmetric fashion and thus, some groups of workers do suffer more from fluctuations: the Poor (e.g., Storesletten et al., 2001b) the Unemployed (e.g., Krusell and Smith, 1999 or Krebs, 2007).

A challenge for the analysis of the costs of business cycles is that an assumption needs to be made with respect to the counterfactual income, i.e., the income after removing aggregate fluctuations. The model presented here provides a natural reference point, namely the non-stochastic steady state of the economy. In order to elicit the role that mobility costs play for the welfare costs of aggregate fluctuations, I discuss an alternative version of the model which features full insurance against asymmetric income fluctuations via pooling cross-sectionally all incomes in a family structure.[3] The income streams

[2]In a parallel line of research, several papers developed multisectoral real business cycle models that feature both aggregate shocks and sectoral shocks and the goal is to identify the role of each of the two (e.g., Horvath, 1998, 2000; or more recently Foerster et al., 2011) . A main feature of those models is that the production technologies of the several sectors are interrelated via input-output linkages and thus some of the shocks observed as aggregate shocks through the naive lense of a one-sector model might in fact reflect sector-specific shocks that did not cancel out across sectors. Further, labor is completely mobile in those models.

[3]The general idea that the family chooses on behalf of its members is in the spirit of the employment

generated in this economy can then serve as an additional reference point.

It must be noted that the focus of the chapter is on the description of the model economy and the illustration of how it can be used in the context of analyzing the welfare costs of business cycles. An actual calculation of the latter is only reasonable in a properly calibrated version of the model, which is left for future research.

The chapter is organized as follows. Section 5.2 discusses a version of the model without unemployment and Section 5.3 introduces unemployment into the model. Section 5.4 briefly illustrates the model numerically, before Section 5.5 discusses how the model can be used in the context of analyzing the welfare costs of business cycles. Section 5.6 concludes.

5.2 Model Economy Without Unemployment

5.2.1 Intraperiod Equilibrium

Firms

Firms in sector i produce with a Cobb-Douglas technology function

$$f_i\left(n_i^f, z\right) = zn^{\alpha_i},\ z > 0,\ \alpha_i \in (0, 1]$$

where n_i^f is the labor input to production in sector i. In equilibrium this will be the number of workers in sector i, N_i, times the individual labor supply - workers in one sector are homogenous and hence supply the same amount of labor. The elasticity of labor in production, α_i, is assumed to be identical in the two submarkerts.[4] Productivity z follows an AR(1) process with mean one. Firms are price-takers and thus in each sector the firm's optimum is characterized by

$$f_i'\left(n_i^f, z\right) = w_i \tag{5.1}$$

Profits in units of the good produced in the sector are given by $\pi_i = f_i\left(n_i^f, z\right) - f_i'\left(n_i^f, z\right) n_i^f$.

lotteries of Rogerson (1988).

[4]Different curvatures of the production technologies lead to asymmetric propagation of the aggregate technology shock via the supply-side of the economy similar to non-homothetic preferences. The two alternatives will have different implications for the reaction of relative prices to an aggregate shock. Throughout the chapter, we focus on the demand-side channel, i.e., the case with non-homothetic preferences as discussed below.

Workers

Workers enjoy utility from consumption of the two consumption goods and from leisure. Effort exerted to switch sectors implies a direct utility cost $k(e_i)$. Overall, per-period utility is given by

$$u^i = u\left(c_1^i, c_2^i\right) + v\left(1 - n^i\right) - k\left(e_i\right), \tag{5.2}$$

where c_1^i and c_2^i is the demand of a worker in sector i for good 1 and 2, respectively, n_i denotes labor supply (the time endowment of a household is normalized to 1) and e_i is excerted switching effort. The utility function $u(c1, c2)$ is increasing with decreasing marginal utility in c_1^i and c_2^i, and is non-homothetic in the two goods. The assumption of additive separable effort costs implies that the intertemporal optimization (via choice of the switching effort) does not affect the intraperiod decision problem (labor supply and consumption) and thus the intraperios problem can be separated.

The budget set of the two groups of workers in a given period is

$$\begin{aligned} c_1^1 + p_2 c_2^1 &\leq w_1 n^1 + \frac{\pi_1}{N_1} && (5.3a) \\ c_1^2 + p_2 c_2^2 &\leq p_2\left(w_2 n^2 + \frac{\pi_2}{N_2}\right), && (5.3b) \end{aligned}$$

where p_2 is the relative price of good 2 and w_i is the real wage in sector i measured in units of the good produced. π_i is the sector's profit per head: it is assumed that in each period profits in a sector are distributed amongst the population of that sector.[5]

The following set of first order conditions with respect to consumption and labor supply characterize the workers' intraperiod optimum.

$$\begin{aligned} u_1\left(c_1^1, c_2^1\right) - \lambda_1 &= 0 && (5.4a) \\ u_2\left(c_1^1, c_2^1\right) - \lambda_1 p_2 &= 0 && (5.4b) \\ -v'\left(1 - n^1\right) - \lambda_1 w_1 &= 0 && (5.4c) \\ w_1 n^1 + \frac{\pi_1}{N_1} - c_1^1 - p_2 c_2^1 &= 0 && (5.4d) \\ u_1\left(c_1^2, c_2^2\right) - \lambda_2 &= 0 && (5.4e) \\ u_2\left(c_1^2, c_2^2\right) - \lambda_2 p_2 &= 0 && (5.4f) \\ -v'\left(1 - n^2\right) - \lambda_2 w_2 p_2 &= 0 && (5.4g) \\ p_2\left(w_2 n_2 + \frac{\pi_2}{N_2}\right) - c_1^2 - p_2 c_2^2 &= 0 && (5.4h) \end{aligned}$$

[5]This is equivalent to a constant nonlabor input to production which is owned by the workers of a sector and rented by the firms.

where λ_1 and λ_2 are the Lagrange multipliers attached to the constraints. For a given relative price p_2 the excess demands for the two goods are

$$
\begin{aligned}
ex_1(p_2) &= N_1 c_1^1(p_2) + N_2 c_1^2(p_2) - f_1\left(N_1 n^1(p_2), z\right) && (5.5a)\\
ex_2(p_2) &= N_1 c_2^1(p_2) + N_2 c_2^2(p_2) - f_2\left(N_2 n^2(p_2), z\right) && (5.5b)
\end{aligned}
$$

Definition 5.1 ***Intraperiod Equilibrium:*** *The intraperiod equilibrium for given state of the economy (N_1, N_2, z) is a list of prices and wages (p_2, w_1, w_2) such that for the corresponding optimal plans of firms and households, markets clear. One can obtain the equilibrium values of $(c_1^{1*}, c_2^{1*}, c_1^{2*}, c_2^{2*}, n^{1*}, n^{2*}, p_2^*)$ as functions of (N_1, N_2, z) by first solving the FOCs (5.4) and (5.1) for a given relative price p_2 for $(c_1^1(p_2), c_2^1(p_2), c_1^2(p_2), c_2^2(p_2), n^1(p_2), n^2(p_2))$. The equilibrium relative price p_2^* solves $ex_1(p_2^*) = ex_2(p_2^*) = 0$.*

5.2.2 Intertemporal Problem

Given a mass of workers $\bar{N}$, there is one aggregate endogenous state variable N_1 and one exogenous state variable z. The firms' planning horizon is one period and they simply solve their intratemporal problem in each period. The household decision is intertemporal: expectations such that being in the other sector has a higher expected lifetime utility motivate an household to exert switching effort, which translates into a switching probability. The timing assumption is that in a given period the household is in one sector and solves the intraperiod decision problem. At the end of the period, that is after profit shares are distributed, he or she can exert effort e at cost $k(e)$ and with the resulting probability $\psi(e)$ immediately switch the sector.

I assume convex effort costs: $k'(e) > 0$, $k''(e) > 0$ and $k'(0) = 0$. The probability function maps from $\mathbb{R}_+$ into $[0, 1)$ and is increasing: $\psi'(e) > 0$. We further assume that $\lim_{e\to 0} \psi'(e) \in \mathbb{R}_+$. Households base their decision on an assumption about the aggregate law of motion $G(N_1, z)$, which gives tomorrow's expected number of workers in sector 1 as a function of todays number of workers N_1 and todays aggregate productivity z.

The recursive household problem is given by

$$
\begin{aligned}
V^1(N_1, z) = \max_{e^1 \geq 0} \Big[& u\left(c_1^{1*}, c_2^{1*}\right) + v\left(1 - n^{1*}\right) - k\left(e^1\right) + \\
& \psi\left(e^1\right) \beta E_{z'|z} V^2\left(G(N_1, z), z'\right) + \left(1 - \psi\left(e^1\right)\right) \beta E_{z'|z} V^1\left(G(N_1, z), z'\right) \Big] \qquad (5.6a)
\end{aligned}
$$

$$V^2(N_1,z) = \max_{e^2\geq 0}\Big[u\left(c_1^{2*},c_2^{2*}\right) + v\left(1-n^{2*}\right) - k\left(e^2\right) + \\ \psi\left(e^2\right)\beta E_{z'|z}V^1\left(G\left(N_1,z\right),z'\right) + \left(1-\psi\left(e^2\right)\right)\beta E_{z'|z}V^2\left(G\left(N_1,z\right),z'\right)\Big] \quad (5.6b)$$

where $(c_1^{1*}, c_2^{1*}, c_1^{2*}, c_2^{2*}, n^{1*}, n^{2*})$ are the intraperiod equilibrium values as defined above for the state (N_1, z). The first order conditions for an interior solution with respect to effort are

$$\frac{k'\left(e^1\right)}{\psi'\left(e^1\right)} = \beta E_{z'|z}\Big(V^2\left(G\left(N_1,z\right),z'\right) - V^1\left(G\left(N_1,z\right),z'\right)\Big) \quad (5.7a)$$

$$\frac{k'\left(e^2\right)}{\psi'\left(e^2\right)} = \beta E_{z'|z}\Big(V^1\left(G\left(N_1,z\right),z'\right) - V^2\left(G\left(N_1,z\right),z'\right)\Big) \quad (5.7b)$$

The corner solution $e^i = 0$ is chosen whenever the expected value difference from moving into the other sector is less or equal to zero. The assumptions on the cost function $k(e)$ and the switching technology $\psi(e)$ are such that a unique solution exists and that zero effort is chosen only when the expected value difference is zero or negative. There never is positive switching effort in both sectors at the same time and it always holds that either e^1 is zero, or e^2 is zero, or both: in every period labor market movements are one-directional.

Definition 5.2 ***Recursive Equilibrium:*** *A recursive equilibrium of the economy consists of the value functions $V^1(N_1,z)$ and $V^2(N_1,z)$, the policy functions $e^1(N_1,z)$ and $e^2(N_1,z)$ and an aggregate law of motion $G(N_1,z)$ such that*

1. *Given $G(N_1,z)$, $V^1(N_1,z)$ and $V^2(N_1,z)$ solve the Bellman equations of the households and $e^1(N_1,z)$ and $e^2(N_1,z)$ are the corresponding optimal policies.*

2. *The law of motion $G(N_1,z)$ satisfies*
   $G(N_1,z) = (1-\psi(e^1(N_1,z)))N_1 + \psi(e^2(N_1,z))\left(\bar{N}-N_1\right)$

5.3 Introducing Unemployment Into the Model

Building on the depicted model, I now introduce unemployment, which adds a state variable to the model. During unemployment, workers enjoy home production. A worker in the unemployment pool excerts effort in order to leave unemployment, which translates into a probability of transitioning to employment. An unemployed worker's search is directed towards the sector which he or she prefers; hence, there is no random matching to sectors. This describes the flow out of the unemployment pool.[6]

[6]The search technology that translates an unemployed worker's search effort into a job finding probability determines the average unemployment duration.

Inflow into unemployment consists of those workers that in a period lose employment in either sector, which occours with an exogenous probability that depends on the state of the aggregate productivity. Unemployed workers draw utility from home production. In contrast to benefits dependening on former wages this assumption implies homogeneity of the unemployed.[7]

With regard to timing, we assume that switching occurs after production, but before the arrival of the unemployment shock. This implies that the intertemporal (effort) decision of a currently employed worker is unaffected by the presence of the separation shock - in the sense that for a given expected value difference the effort decision is the same. Denoting the separation shock in sector i by $s_i(z)$, the value functions of workers are as follows.

$$\begin{aligned} V^1(N_1,U,z) = \max_{e^1\geq 0}\Big[& u\left(c_1^{1*},c_2^{1*}\right)+v\left(1-n^{1*}\right)+s_1(z)\,\beta E_{z'|z}V^U\left(G(N_1,U,z),z'\right)+ \\ & (1-s_1(z))\Big(-k\left(e^1\right)+\psi_e\left(e^1\right)\beta E_{z'|z}V^2\left(G(N_1,U,z),z'\right)+ \\ & \left(1-\psi_e\left(e^1\right)\right)\beta E_{z'|z}V^1\left(G(N_1,U,z),z'\right)\Big)\Big] \end{aligned} \tag{5.8a}$$

$$\begin{aligned} V^2(N_1,U,z) = \max_{e^2\geq 0}\Big[& u\left(c_1^{2*},c_2^{2*}\right)+v\left(1-n^{2*}\right)+s_2(z)\,\beta E_{z'|z}V^U\left(G(N_1,U,z),z'\right)+ \\ & (1-s_2(z))\Big(-k\left(e^2\right)+\psi_e\left(e^2\right)\beta E_{z'|z}V^1\left(G(N_1,U,z),z'\right)+ \\ & \left(1-\psi_e\left(e^2\right)\right)\beta E_{z'|z}V^2\left(G(N_1,U,z),z'\right)\Big)\Big] \end{aligned} \tag{5.8b}$$

Notation is modified slightly compared to the case without unemployment. The switching technology of an employed worker is now denoted by $\psi_e(\cdot)$ and the expected aggregate law of motion $G(\cdot)$ describes the expected transition of the population as a function that maps from the state of the world into a vector (N_1', U') $(G(N_1,U,z) : [0,1]\times[0,1]\times\mathbb{R}\rightarrow [0,1]\times[0,1])$. The decision problem of the workers is symmetric to the case without

[7] If benefits depend on the last wage, symmetric linear technology in the two sectors implies homogeneity w.r.t. benefits of workers becoming unemployed in a period. Heterogeneity in the unemployment pool stems from unemployment beginning in different periods.

unemployment. V^u denotes the value function of an unemployed worker:

$$V^u(N_1, U, z) = \max_{e^u \geq 0} \Big[u\left(\overline{c_1^u}, \overline{c_2^u}\right) - k(e^u) + \psi_u(e^u)\,\beta E_{z'|z} \max\left\{V^1(G(N_1, U, z), z'), V^2(G(N_1, U, z), z')\right\} + (1 - \psi_u(e^u))\,\beta E_{z'|z} V^u(G(N_1, U, z), z') \Big] \quad (5.8c)$$

The period utility $u\left(\overline{c_1^u}, \overline{c_2^u}\right)$ corresponds to the value of home production. In each period an unemployed decides how much effort to spend in order to leave unemployment. This decision is based on expectations about the value of being in either sector next period. Effort e^u translates into a probability $\psi_u(e^u)$ of leaving unemployment towards the sector which in expectation gives a higher value to a worker next period. An expected value difference of zero by assumption implies a random distribution of newly employed to the two sectors in equal shares.

In the context of this specification, in each period one sector is the receiver of worker flows, both from unemployment and from the other sector. The first-order conditions are

$$\frac{k'(e^1)}{\psi_e'(e^1)} = \beta E_{z'|z} \Big(V^2(G(N_1, U, z), z') - V^1(G(N_1, U, z), z') \Big) \quad (5.9a)$$

$$\frac{k'(e^2)}{\psi_e'(e^2)} = \beta E_{z'|z} \Big(V^1(G(N_1, U, z), z') - V^2(G(N_1, U, z), z') \Big) \quad (5.9b)$$

$$\frac{k'(e^u)}{\psi_u'(e^u)} = \beta E_{z'|z} \Big(\max\left\{V^1(G(N_1, U, z), z'), V^2(G(N_1, U, z), z')\right\} - V^u(G(N_1, U, z), z') \Big) \quad (5.9c)$$

5.4 Numerical Illustration of the Model

This section serves to illustrate the main mechanism of the model economy. The elements of the per-period utility function (5.2) are specified as follows. Utility from consumption is the sum of two CRRA utility functions:

$$u\left(c_1^i, c_2^i\right) = \frac{\left(c_1^i\right)^{1-\gamma_1}}{1-\gamma_1} + \phi_2 \frac{\left(c_2^i\right)^{1-\gamma_2}}{1-\gamma_2}, \quad (5.10)$$

Table 5.1: Illustrative Parametrization

utility		technology	
β	0.99	ρ_z	0.95
γ_1	1	σ_z	*0.015*; 0.03
γ_2	2	α_1, α_2	1
γ_n	1	ε_{eff}	5
ϕ_2	1	ϕ_{eff}, ϕ^u_{eff}	10000, 1000
ϕ_n	1		

Note: Table shows the parameter values picked for the illustration of the model.

the utility from leisure is

$$v\left(1-n^i\right) = \phi_n \frac{\left(1-n^i\right)^{1-\gamma_n}}{1-\gamma_n}, \tag{5.11}$$

with $\phi_2, \phi_n, \gamma_1, \gamma_2, \gamma_n > 0$, where ϕ_2 and ϕ_n are weighting parameters of utility from consumption good 2 and leisure, respectively. The felicity function is non-homothetic in the two consumption goods when $\gamma_1 \neq \gamma_2$. The cost of switching effort measured in units of period-utility and the switching technology are specified as

$$k\left(e\right) = \frac{\phi_{eff}}{1+\varepsilon_{eff}} e^{1+\varepsilon_{eff}}, \ \varepsilon_{eff} > 0, \phi_{eff} > 0 \tag{5.12a}$$

$$\psi\left(e\right) = 1 - \exp\left(-e\right) \tag{5.12b}$$

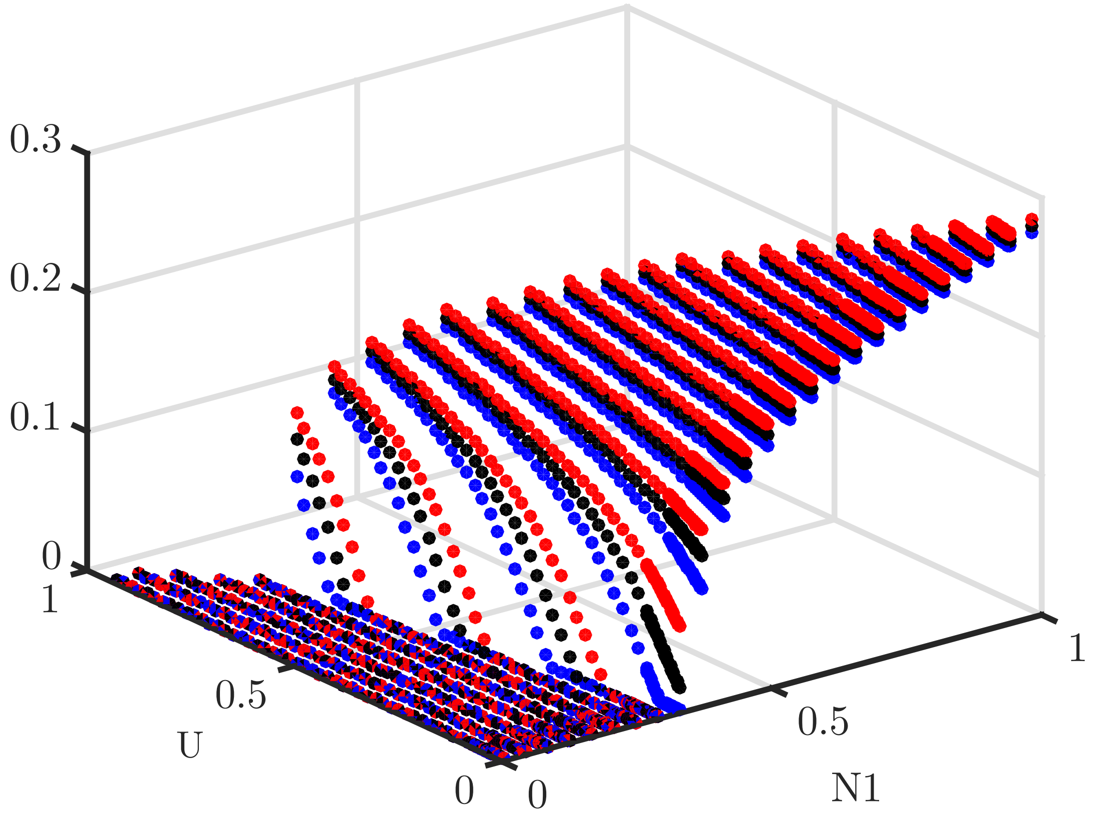
I solve the model for an illustrative parameterization (see Table 5.1). Figure 5.1 plots the search effort policy functions $e^1(N_1, U, z)$ and $e^2(N_1, U, z)$. Effort is excerted by workers in one market only. The asymmetric propagation of the aggregate fluctuations to the two sectors via the non-homothetic demand structure is apparent by the way the policy functions vary with aggregate productivity: Workers in sector 1 excert more search effort when aggregate productivity is low, for workers in sector 2 it is the other way around.

5.5 Welfare Costs of Aggregate Risk

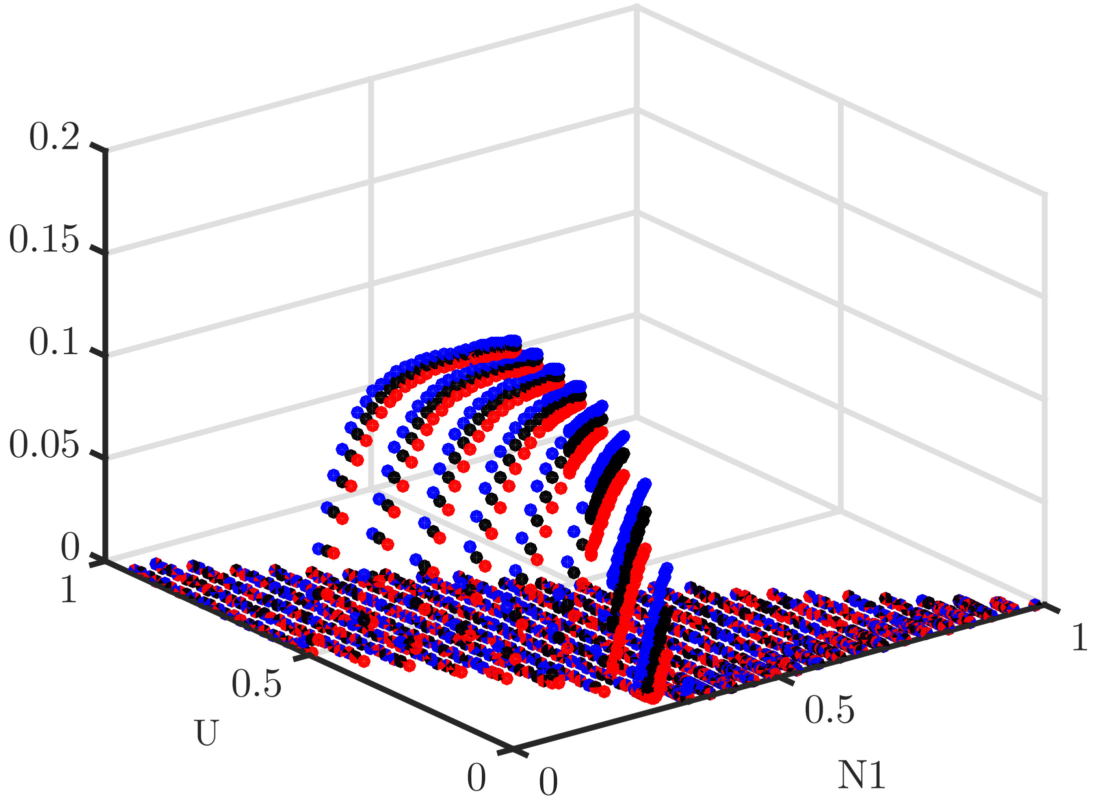
In the context of the model economiy one can evaluate the welfare costs of business cycles in a framework that explicitly generates asymmetric wage responses from aggregate fluctuations. In the vein of Lucas, the welfare costs of business cycles can be calculated by asking how consumers in a risky world have to be compensated in order to be indifferent

Figure 5.1: Search Effort Excerted by Workers in Each Sector

(a) Workers in sector 1



(b) Workers in sector 2



Note: Each panel shows the search effort policy function for 3 different values of the aggregate productivity: low (red), medium (black), high (blue).

to a risk-free world. Studies of the welfare costs of business cycles usually assume that eliminating business cycles does not change the average level of income. Taking this assumption to our model, we leave the exogenous technology shock z, the driver of business cycles, at its unconditional expectation and solve for the non-stochastic steady state of our model, which then serves as reference point for welfare evaluation.

5.5.1 The Non-Stochastic Steady State

In the steady state for a given value of productivity z, the value of being employed in either sector has to be the same to ensure that there are no transitions between the two markets: there cannot be a steady state with labor market transitions between the two sectors, because the loss of workers in one sector would not be compensated by newly employed, who move to the more attractive sector. The following equations have to hold (for brevity dependency on z is surpressed).

$$
\begin{aligned}
s_1 N_1 &= p\psi_e\left(e^u\right)U && \text{(5.13a)}\\
s_2 N_2 &= \left(1-p\right)\psi_e\left(e^u\right)U && \text{(5.13b)}\\
N_1+N_2+U &= \bar{N}, && \text{(5.13c)}
\end{aligned}
$$

where p denotes the share of newly employed moving to sector one. Switching between the two sectors must not be profitable and hence the following equality has to hold:

$$
\begin{aligned}
&u\left(c_1^{1*}\left(N_1,U\right),c_2^{1*}\left(N_1,U\right)\right)+v\left(1-n^{1*}\left(N_1,U\right)\right)+s_1\beta V^U\left(N_1,U\right)=\\
&\qquad u\left(c_1^{2*}\left(N_1,U\right),c_2^{2*}\left(N_1,U\right)\right)+v\left(1-n^{2*}\left(N_1,U\right)\right)+s_2\beta V^U\left(N_1,U\right) \quad \text{(5.14)}
\end{aligned}
$$

Notice the appearence of $V^u(\cdot)$ in equation (5.14): if the risk of becoming unemployed differs by sector ($s_1 \neq s_2$), this risk difference needs to be compensated by per-period utility. When unemployment risk is the same, the condition states that felicities in the two sectors have to be the same - as would be the case without unemployment.

Denoting the deterministic steady state values by superscript d, the present-value lifetime utility of a households in the two sectors is denoted by U_1^d and U_2^d.

5.5.2 Costs of Business Cycles

In order to achieve the most straightforward comparability to the calculation in Lucas (1987), I focus on a consumption equivalent variation as the relevant measure of welfare comparison. Since there are several goods, I interpret the non-homothetic utility function as a consumption aggregate and compensate the household in units of this aggregate.[8]

In order to evaluate how workers in different sectors are hit in the presence of mobility costs, I distinguish workers by their initial sector affiliation. Applying an ex ante perspective, the welfare measure is calculated by equating the expected value of being in either sector to the present-value utility of a worker in the risk-free economy. The respective consumption equivalent variations are implicitly given by:

$$E_{z,N_1} V^1 (N_1, U, z, \lambda_1) = U_1^d \tag{5.15a}$$

$$E_{z,N_1} V^2 (N_1, U, z, \lambda_2) = U_2^d, \tag{5.15b}$$

where $V^1 (N_1, U, z, \lambda_1)$ and $V^2 (N_1, U, z, \lambda_2)$ are the value functions of being in sector 1 and 2, respectively, that add the proportional compensation to each periods utility: a household that now is in sector i gets proportional compensation λ_i on the lifetime path of consumption. E_{z,N_1} is the expectation operator that gives the unconditional expectaion over the joint distribution of the exogenous technology and the endogenous labor allocation.

$V^1 (N_1, U, z, \lambda_1)$ and $V^2 (N_1, U, z, \lambda_2)$ are given by

$$\begin{aligned} V^1 (N_1, U, z, \lambda_1) = \Big[& (1+\lambda_1) u \left(c_1^{1*}, c_2^{1*}\right) + v \left(1 - n^{1*}\right) - k \left(e^{1*}\right) + \\ & \psi \left(e^{1*}\right) \beta E_{z'|z} V^2 \left(G \left(N_1 U, z\right), z', \lambda_1\right) + \\ & \left(1 - \psi \left(e^{1*}\right)\right) \beta E_{z'|z} V^1 \left(G \left(N_1, U, z\right), z', \lambda_1\right) \Big] \end{aligned} \tag{5.16a}$$

$$\begin{aligned} V^2 (N_1, U, z, \lambda_2) = \Big[& (1+\lambda_1) u \left(c_1^{2*}, c_2^{2*}\right) + v \left(1 - n^{2*}\right) - k \left(e^{2*}\right) + \\ & \psi \left(e^{2*}\right) \beta E_{z'|z} V^1 \left(G \left(N_1, U, z\right), z', \lambda_2\right) + \\ & \left(1 - \psi \left(e^{2*}\right)\right) \beta E_{z'|z} V^2 \left(G \left(N_1, U, z\right), z', \lambda_2\right) \Big]. \end{aligned} \tag{5.16b}$$

5.5.3 Reference Point: Perfect Insurance

The model does not feature assets. This implies that the above measures of the welfare costs of aggregate fluctuations overstate the actual costs, because workers cannot insure

[8] A second possibility is a compensation in income that the households can spend optimally, equilibrium prices given, which is straighforward to implement here.

themselves against income fluctuations. Further, the goal is to extract the specific role for welfare played by the mobility costs that inhibit workers to immediately respond to asymmetric wage changes. To this end, I now consider another extreme: perfect insurace of households against asymmetric wage changes and unemployment. The overall structure of the economy is the same, with the one difference that all workers are part of a family that consists of a mass of workers–and the economy is populated by a mass of families. The focus here is on the characterization of the solution of the family's problem. The utility derived from the consumption stream of the family is then a natural point of comparison for the evaluation of the role of mobility costs for the welfare implications of aggregate fluctuations: the family faces the same mobility costs for its workers as workers in the economy without risk-sharing.

A family is described by two endogenous state variables: its allocation of workers to sectors and unemployment, N_1 and U, as well as two aggregate state variables: aggregate productivity z and the aggregate distribution of families, denoted by ϕ. ϕ is a distribution of families over their allocation of workers, which is an equilibrium object. A family pins down the labor supply and the switching effort exerted by its members. Within a family, all incomes are pooled.

Intraperiod Equilibrium

Family i's intraperiod problem is

$$\begin{aligned} \max_{\substack{c_{1i}, c_{2i}, \\ n_{1i}, n_{2i}}} u\left(c_{1i}, c_{2i}\right) + N_{1i} v\left(1-n_{1i}\right) + \left(1-N_{1i}-U_i\right) v\left(1-n_{2i}\right) \\ + U_i v\left(1\right) \\ s.t.\ c_{1i} + p_2 c_{2i} \leq w_1 N_{1i} n_{1i} + p_2 w_2 \left(1-N_{1i}-U_i\right) n_{2i} \end{aligned} \tag{5.17}$$

The aggregate labor supply in sectors 1 and 2 is $\int N_{1i} n_{1i} d\Phi$ and $\int N_{2i} n_{2i} d\Phi$, respectively. Equilibrium supplies solve the representative firms' first order conditions for an interior solution:

$$\begin{aligned} \frac{\partial f_1\left(\int N_{1i} n_{1i}^* d\Phi, z\right)}{\partial n} &= w_1^* \\ \frac{\partial f_2\left(\int N_{2i} n_{2i}^* d\Phi, z\right)}{\partial n} &= w_2^* \end{aligned}$$

Intertemporal Problem

The value function of family i is given by

$$V_i\left(N_{1i},U_i,z,\Phi\right)=\max_{e_{1i},e_{2i},e_{ui}}\Big[r\left(N_{1i},U_i,z,\Phi\right)-N_{1i}\left(1-s_1\left(z\right)\right)k_e\left(e_{1i}\right)- \left(1-N_{1i}-U_i\right)\left(1-s_2\left(z\right)\right)k_e\left(e_{2i}\right)-U_ik_u\left(e_{ui}\right)+ \beta EV_i\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right) \quad (5.18)$$

$$\begin{aligned}
V_i\left(N_{1i},U_i,z,\Phi\right) &= \max_{e_{1i},e_{2i},e_{ui}}\Big[r\left(N_{1i},U_i,z,\Phi\right)-N_{1i}\left(1-s_1\left(z\right)\right)k_e\left(e_{1i}\right)- \\
&\quad \left(1-N_{1i}-U_i\right)\left(1-s_2\left(z\right)\right)k_e\left(e_{2i}\right)-U_ik_u\left(e_{ui}\right)+ \\
&\quad \beta EV_i\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right) \\
s.t. & \\
N'_{1i} &= \left(1-s_1\left(z\right)\right)\left(1-\psi_e\left(e_{1i}\right)\right)N_{1i}+\left(1-s_2\left(z\right)\right)\psi_e\left(e_{2i}\right)\left(1-N_{1i}-U_i\right) \\
&\quad +\mathbb{1}_i^{EV_{i1}}\psi_u\left(e_{ui}\right)U_i \\
U'_i &= \left(1-\psi_u\left(e_{ui}\right)\right)U_i+s_1\left(z\right)N_{1i}+s_2\left(z\right)\left(1-N_{1i}-U_i\right)
\end{aligned}$$

where

$$r\left(N_{1i},U_i,z,\Phi\right)=u\left(c^*_{1i},c^*_{2i}\right)+N_{1i}v\left(1-n^*_{1i}\right)+\left(1-N_{1i}-U_i\right)v\left(1-n^*_{2i}\right)+U_iv\left(1\right) \quad (5.19)$$

and $\left(c^*_{1i},c^*_{2i},n^*_{1i},n^*_{2i}\right)$ solve the family's intraperiod maximization problem in the intraperiod equilibrium in state $\left(N_{1i},U_i,z,\Phi\right)$. The indicator variable $\mathbb{1}_i^{EV_{i1}}$ takes on the value 1 if $EV_{i1}\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right)>0$ and 0 otherwise. The first order condtions for the above Bellman equation (5.18) are

$$k'_e\left(e_{1i}\right) = \psi'_e\left(e_{1i}\right)\times\Big(-\beta EV_{i1}\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right)\Big) \quad (5.20a)$$

$$k'_e\left(e_{2i}\right) = \psi'_e\left(e_{2i}\right)\times\Big(\beta EV_{i1}\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right)\Big) \quad (5.20b)$$

$$k'_u\left(e_{ui}\right) = \psi'_u\left(e_{ui}\right)\times\beta E\Big(\mathbb{1}_i^{EV_{i1}}V_{i1}\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right) -V_{i2}\left(N'_{1i},U'_i,z',G\left(\Phi\right)\right)\Big) \quad (5.20c)$$

where $V_{ij}\left(\cdot\right)$ denotes the derivative of the value function $V_i\left(\cdot\right)$ with respect to the j'th argument. As in the case of no insurance, there is a corner solution for e_{1i} or e_{2i}. Using the envelope theorem one can write these derivatives as

$$\begin{aligned} V_{i1}\left(N_{1i},U_i,z,\Phi\right) &= v\left(1-n_{1i}^*\right)-v\left(1-n_{2i}^*\right)-\left(k_e\left(e_{1i}^*\right)-k_e\left(e_{2i}^*\right)\right) && (5.21a)\\ &+ \mu_i^*\left(w_1^*n_{1i}^*-w_2^*p_2^*n_{2i}^*\right)\\ &+ \lambda_{i1}^*\left[\left(1-s_1\left(z\right)\right)\left(1-\psi_e\left(e_{1i}^*\right)\right)-\left(1-s_2\left(z\right)\right)\psi_e\left(e_{2i}^*\right)\right]\\ &+ \lambda_{i2}^*\left[s_1\left(z\right)-s_2\left(z\right)\right]\\ V_{i2}\left(N_{1i},U_i,z,\Phi\right) &= v\left(1\right)-v\left(1-n_{2i}^*\right)-\left(k_e\left(e_{ui}^*\right)-k_e\left(e_{2i}^*\right)\right) && (5.21b)\\ &+ \mu_i^*\left(-w_2^*p_2^*n_{2i}^*\right)+\lambda_{i1}^*\left[\mathbb{1}_i^{EV_{i1}}\psi_u\left(e_{ui}^*\right)-\left(1-s_2\left(z\right)\right)\psi_e\left(e_{2i}^*\right)\right]\\ &+ \lambda_{2i}^*\left[\left(1-\psi_u\left(e_u^*\right)\right)-s_2\left(z\right)\right] \end{aligned}$$

with μ_i^* denoting the value of the Lagrange multiplier on family i's budget constraint in the intraperiod equilibrium in state (N_{1i}, U_i, z, Φ) and λ_{i1}^* and λ_{i2}^* denoting the equilibrium values of the multipliers on the laws of motion.

If in the initial period, the allocation of workers is the same for every family, i.e. there is no heterogeneity of families, the distribution $\Phi_{t=0}$ is degenerate and the following holds in the initial period: $N_{1i} = N_{1j}$ and $U_i = U_j$ $\forall i, j$. It follows that the choices $(c_{1i}, c_{2i}, n_{1i}, n_{2i}, e_{1i}, e_{2i}, e_{ui}) = (c_{1j}, c_{2j}, n_{1j}, n_{2j}, e_{1j}, e_{2j}, e_{uj})$ $\forall i, j$. This implies that the law of motion for the labor allocation is the same for all families and hence next period's distribution $\Phi_{t=1}$ is degenerate. As the same argument holds for each period, there is no heterogeneity of families in the recursive equilibrium when adding the initial condition that $\Phi_{t=0}$ is degenerate. The household side of the economy can hence be desribed by a representative family with the following recursive optimization problem:

$$\begin{aligned} V\left(N_1,U,z\right) &= \max_{e_1,e_2,e_u}\Big[r\left(N_1,U,z\right)-N_1\left(1-s_1\left(z\right)\right)k_e\left(e_1\right)- && (5.22)\\ &\quad \left(1-N_1-U\right)\left(1-s_2\left(z\right)\right)k_e\left(e_2\right)-\\ &\quad Uk_u\left(e_u\right)+\beta EV\left(N_1',U',z'\right)\Big]\\ s.t.&\\ N_1' &= \left(1-s_1\left(z\right)\right)\left(1-\psi_e\left(e_1\right)\right)N_1+\left(1-s_2\left(z\right)\right)\psi_e\left(e_2\right)\left(1-N_1-U\right)\\ &\quad +\mathbb{1}_i^{EV_{i1}}\psi_u\left(e_u\right)U\\ U' &= \left(1-\psi_u\left(e_u\right)\right)U+s_1\left(z\right)N_1+s_2\left(z\right)\left(1-N_1-U\right) \end{aligned}$$

where

$$r(N_1, U, z) = u(c_1^*, c_2^*) + N_1 v(1 - n_1^*) + (1 - N_1 - U) v(1 - n_2^*) + Uv(1) \tag{5.23}$$

and $(c_1^*, c_2^*, n_1^*, n_2^*)$ solve the family's intraperiod maximization problem in the intraperiod equilibrium in state (N_1, U, z). The intraperiod solution simplifies accordingly.

5.6 Conclusion

This chapter introduces a multisectoral real business cycle model. The focus lies on the illustration of a mechanism that propagates an aggregate shock asymmetrically across groups of workers. The specific channel analyzed is that the relative demand for the goods produced in different sectors changes with aggregate income due to preferences that are non-homothetic with respect to the goods produced in the different sectors. Worker mobility between sectors is imperfect and thus wages respond asymmetrically to the aggregate shock. I then discussed how the model framework can be used in principle to analyze the welfare costs of aggregate fluctuations.

Appendix A

Appendices to Chapter 2

A.1 Simplifying the Value Functions

An implication of the taste shocks is that it simplifies the value functions–relative to a version of the model without these shocks. Technically speaking, I get rid of kinks in the value functions V^{stay}, V^{offer}, and V^{unempl} that are induced by the discrete choices and am left with continuous value functions. I impose $F_{\mathbb{O}}$ to be a Gumbel distribution with scale parameter $\sigma_{\mathbb{O}}$ and location parameter $-\sigma_{\mathbb{O}}\gamma$, where γ is Euler's constant. The location parameter is a normalization such that the unconditional expected value of each taste shock is zero. Using Gumbel iid taste shocks allows me to exploit results from discrete choice theory, as also done in, e.g., Pilossoph (2014) or Iskhakov et al. (2015). Gumbel distributed taste shocks yield analytical expressions for the continuation values conditional on the state vector $(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$.

First, consider the (expected) continuation values in equations (2.10) and (2.11): the worker does not control $o_{i,t}$, which is a state. The expected value of the taste shock is thus the unconditional expected value of $F_{\mathbb{O}}$, which is normalized to zero. By independence of the productivity and taste shocks, this gives

$$\begin{aligned} V^{empl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) = \phi \times \Bigg(& \psi^{e} \times V^{offer}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) + \dots \\ & (1-\psi^{e}) \times V^{stay}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) \Bigg) + \dots \\ & (1-\phi) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E V^{unempl}\left(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right) \right) \end{aligned} \tag{A.1}$$

and

$$V^{stay}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right) = \widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t},\tilde{h}_{i,t+1}\right)+\ldots \qquad \text{(A.2)}$$
$$\widetilde{\beta}EV^{empl}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right).$$

In the following, I only explicitly state the state variables η and o for readability. The expected continuation value of entering next period as an employed worker is

$$EV^{empl}\left(\boldsymbol{\eta}_{i,t+1},o_{i,t}\right)=\phi\times\left(\psi^{e}\times E_{\boldsymbol{\eta}}V^{offer}\left(\boldsymbol{\eta}_{i,t+1},o_{i,t+1}\right)+\ldots\right.$$
$$\left.(1-\psi^{e})\times E_{\boldsymbol{\eta}}V^{stay}\left(\boldsymbol{\eta}_{i,t+1},o_{i,t+1}\right)\right)+\ldots$$
$$(1-\phi)\times\left(\widetilde{u}^{unempl}+\widetilde{\beta}E_{\boldsymbol{\eta}}V^{unempl}\left(\boldsymbol{\eta}_{i,t+1},o_{i,t+1}\right)\right) \qquad \text{(A.3)}$$

Next, consider the sub value function $V^{offer}(\bullet)$, which in the two value functions (2.10) and (2.13) represents situations in which the worker chooses a target occupation $o_{i,t+1}$. Conditional on sampling occupation j as alternative occupation, the worker chooses to either stay in occupation $o_{i,t}$ or to take the offer from j, maximizing

$$\max\left(\tilde{v}\left(j|\bullet\right)+E_{\mathbb{O}}\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+E_{\mathbb{O}}\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right). \qquad \text{(A.4)}$$

The expectation over taste shocks $\mathbb{O}$ is the expected value of the maximum of the expression. The taste shock can be integrated out to get

$$E_{\mathbb{O}}\left[\max\left(\tilde{v}\left(j|\bullet\right)+\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right)\right].$$

McFadden (1978) shows that the integral over $\mathbb{O}$ can be analytically solved; using his derivation, I write the above expected value as

$$
\begin{aligned}
E_{\mathbb{O}}&\left[\max\left(\tilde{v}\left(j|\bullet\right)+\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right)\right]\\
&=\sigma_{\mathbb{O}}\log\left(\exp\left[\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\frac{-\sigma_{\mathbb{O}}\gamma}{\sigma_{\mathbb{O}}}+\gamma\right)\\
&=\sigma_{\mathbb{O}}\log\left(\exp\left[\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\\
&=\sigma_{\mathbb{O}}\left(\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}+\log\left(1+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)-\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\right)
\end{aligned}
$$

where γ is Euler's constant. This gives the simplified sub value funciton $V^{offer}\left(\bullet\right)$ as:

$$
V^{offer}\left(\bullet\right)=\widetilde{\beta}\times\sum_{j\neq o_{i,t}}\pi_{j}\times\sigma_{\mathbb{O}}\left(\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}+\log\left(1+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)-\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\right), \quad \text{(A.5)}
$$

in which the taste shocks are integrated out and the conditional expectation over the taste shocks has an analytical solution, leaving us with smooth value functions in which only the expectation operator over productivity shocks remains.

A.2 Value Functions for Counterfactual

Consider the welfare experiment in section 2.5.2. Along the lines of equations (2.10) (2.11), and (2.13), the value functions of employed and unemployed workers in the counterfactual world are given by

$$
\begin{aligned}
V^{count}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)=\phi\times&\Big(\widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t},h_{i,t}\right)+\dots\\
&\widetilde{\beta}E\left[V^{count}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]+\dots\\
(1-\phi)\times&\left(\widetilde{u}^{unempl}+\widetilde{\beta}E\left[V^{count-ue}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\right) \quad \text{(A.6)}
\end{aligned}
$$

$$
\begin{array}{lcl}
 & s.t. & \\
x_{i,t+1} & = & g^{e}\left(x_{i,t},o_{i,t},o_{i,t};\boldsymbol{\eta}_{i,t}\right)\\
h_{i,t+1} & \text{acc. to} & (2.7)
\end{array}
$$

$$
\begin{aligned}
V^{count-ue}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right) = \psi^{u}\times\Bigg(&\widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t},\tilde{h}_{i,t+1}\right)+\ldots \\
&\widetilde{\beta}E\left[V^{count}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\Bigg)+\ldots \\
\left(1-\psi^{u}\right)\times\Big(&\widetilde{u}^{unempl}+\widetilde{\beta}E\left[V^{count-ue}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\Big) \qquad \text{(A.7)}
\end{aligned}
$$

$$
\begin{aligned}
&s.t. \\
&x_{i,t+1} \quad = \quad \begin{cases} g^{e}\left(x_{i,t},o_{i,t},o_{i,t};\boldsymbol{\eta}_{i,t}\right) & \text{if empl. in prod. stage of } t \\ x_{i,t} & \text{else} \end{cases} \\
&h_{i,t+1} \quad \text{acc. to} \quad \begin{cases} (2.7) & \text{if empl. in prod. stage} \\ (2.8) & \text{else} \end{cases}
\end{aligned}
$$

A.3 Numerical Solution and Simulation

I solve the model on a discretized state space using global methods. Given a vector of parameters, I use Gaussian quadrature to pick the nodes and weights of the grid for the Normal productivity shocks. For the grid of stochastic productivity, I select the lower (upper) bound to receiving the worst (best) productivity shock five times in a row. I then distribute the grid points with a higher mass of points around the mid-point between lower and upper bound. The grid for human capital is normalized to start at zero and has equidistant grid points; the step size is a parameter.

At every point in the state space, each choice of $o_{i,t+1}$ implies a value of human capital, and a value of idiosyncratic productivity. I locate the point on the grid for idiosyncratic productivity and calculate the linear interpolation weights corresponding to the two surrounding grid points. Together with the exogenous transition probabilities, these weights give an $o_{i,t+1}$–choice specific transition matrix on the whole state space. Given a guess for the value functions, I use the simplified Bellman equations from A.1 to update the value functions. During the calibration stage I iterate until convergence of the policy functions (i.e., the probability to choose any occupation, which is calculated analytically for a given guess of the value functions).

Given the converged policy functions, I combine the policy function with the exogenous transition matrix, which gives a transition matrix over the whole state space as a solution to the model. To get the stationary distribution, I extract (and normalize) the eigenvector with eigenvalue 1 from this transition matrix. To calculate the moments implied by the model in the long run, I directly use the policy functions, which I weight with the stationary distribution over the discrete state space, to calculate the average switching probability and the switching probability as a function of the unemployment duration.

The discretization of the state space implies that I cannot directly use the wage changes implied by the moves on the grid to calculate percentiles of the distribution of wage changes: the calculation of central moments is unproblematic, but there are too few realizations to meaningfully calculate percentiles. I thus distribute N individuals over the discrete state space according to stationary distribution and draw continuous shocks for this sample of workers. One implication of the taste shocks is that the choice probabilities become a smooth function over the state space (net the taste shocks). Thus, I can interpolate the choice probabilities using the policy functions on the discrete grid. Then, I can calculate the wage change for each worker as implied by the choice. Similarly for EUE-transitions, where in addition I take into account that workers transition over the state space during unemployment. I choose a number of N=30,000 individuals for the simulation, repeat the simulation M=3 times, and take the average of the implied moments over the M simulations.

For the calibration, I solve the model at 1,000 parameter combinations, which I choose from a Sobol sequence over the ten-dimensional parameter space. I then calculate the distance as the sum of squared deviations between the model implied moments and the data moments for the selected targets. I choose an identity weighting matrix (reflecting insights in Altonji and Segal (1996), on small sample performance of GMM estimators). I then use the best ten parameter vectors as initial guesses for a simplex downhill minimization algorithm a la Nelder and Mead (1965) to find a minimum. (A more elaborate global minimization procedure is work in progress.)

A.4 Classification of Occupations

The empirical measures of occupational switching are based on occupational segments as defined in the KldB88. The 30 groups are outlined below.

Table A.1: Classification of Occupations

Segment	SIAB group	Description
100	1	Farmers until animal keepers and related occupations
	2	Gardeners, garden workers until forest workers, forest cultivators
200	3	Miners until shaped brick/concrete block makers
301	4	Ceramics workers until glass processors, glass finishers
302	5	Chemical plant operatives
	6	Chemical laboratory workers until vulcanisers
	7	Plastics processors
303	8	Paper, cellulose makers until other paper products makers
	9	Type setters, compositors until printers (flat, gravure)
	10	Special printers, screeners until printer assistants
304	11	Wood preparers until basket and wicker products makers
305	12	Iron, metal producers, melters until semi-finished product fettlers and other mould casting occupations
	13	Sheet metal pressers, drawers, stampers until other metal moulders (non-cutting deformation)
	14	Turners
	15	Drillers until borers
	16	Metal grinders until other metal-cutting occupations
	17	Metal polishers until metal bonders and other metal connectors
	18	Welders, oxy-acetylene cutters
306	19	Steel smiths until pipe, tubing fitters
	20	Sheet metal workers
	21	Plumbers
	22	Locksmiths, not specified until sheet metal, plas-tics fitters
	23	Engine fitters
	24	Plant fitters, maintenance fitters until steel struc-ture fitters, metal shipbuilders
	25	Motor vehicle repairers
	26	Agricultural machinery repairers until precision mechanics
	27	Other mechanics until watch-, clockmakers
	28	Toolmakers until precious metal smiths

	29	Dental technicians until doll makers, model mak-ers, taxidermists
307	30	Electrical fitters, mechanics
	31	Telecommunications mechanics, craftsmen until radio, sound equipment mechanics
	32	Electrical appliance fitters
308	33	Electrical appliance, electrical parts assemblers
	34	Other assemblers
	35	Metal workers (no further specification)
309	36	Spinners, fibre preparers until skin processing operatives
	37	Cutters until textile finishers
310	38	Bakery goods makers until confectioners (pastry)
	39	Butchers until fish processing operatives
	40	Cooks until ready-to-serve meals, fruit, vegetable preservers, preparers
	41	Wine coopers until sugar, sweets, ice-cream makers
311	42	Bricklayers until concrete workers
	43	Carpenters until scaffolders
	44	Roofers
	45	Paviors until road makers
	46	Tracklayers until other civil engineering workers
	47	Building labourer, general until other building labourers, building assistants, n.e.c.
312	48	Stucco workers, plasterers, rough casters until insulators, proofers
	49	Tile setters until screed, terrazzo layers
	50	Room equippers until other wood and sports equipment makers
313	51	Carpenters
314	52	Painters, lacquerers (construction)
	53	Goods painters, lacquerers until ceramics/glass painters
315	54	Goods examiners, sorters, n.e.c.
	55	Packagers, goods receivers, despatchers
316	56	Assistants (no further specification)
317	57	Generator machinists until construction machine attendants
	58	Machine attendants, machinists helpers until ma-chine setters (no further specification)

401	59	Mechanical, motor engineers
	60	Electrical engineers
	61	Architects, civil engineers
	62	Survey engineers until other engineers
	63	Chemists, chemical engineers until physicists, physics engineers, mathematicians
402	64	Mechanical engineering technicians
	65	Electrical engineering technicians until building technicians
	66	Measurement technicians until remaining manu-facturing technicians
	67	Other technicians
	68	Foremen, master mechanics
	69	Biological specialists until physical and mathemat-ical specialists
	70	Chemical laboratory assistants until photo labora-tory assistants
	71	Technical draughtspersons
501	72	Wholesale and retail trade buyers, buyers
	73	Salespersons
	74	Publishing house dealers, booksellers until ser-vice-station attendants
	75	Commercial agents, travellers until mobile traders
502	76	Bank specialists until building society specialists
	77	Health insurance specialists (not social security) until life, property insurance specialists
	78	Forwarding business dealers
	79	Tourism specialists until cash collectors, cashiers, ticket sellers, inspectors
503	80	Railway engine drivers until street attendants
	81	Motor vehicle drivers
	82	Navigating ships officers until air transport occupations
	83	Post masters until telephonists
	84	Warehouse managers, warehousemen
	85	Transportation equipment drivers
	86	Stowers, furniture packers until stores/transport workers
504	87	Entrepreneurs, managing directors, divisional managers

	88	Management consultants, organisors until char-tered accountants, tax advisers
	89	Members of Parliament, Ministers, elected offi-cials until association leaders, officials
	90	Cost accountants, valuers until accountants
	91	Cashiers
	92	Data processing specialists
	93	Office specialists
	94	Stenographers, shorthand-typists, typists until data typists
	95	Office auxiliary workers
505	96	Factory guards, detectives until watchmen, custo-dians
	97	Doormen, caretakers until domestic and non-domestic servants
	98	Soldiers, border guards, police officers until judi-cial enforcers
506	99	Journalists until librarians, archivists, museum specialists
	100	Musicians until scenery/sign painters
	101	Artistic and assisting occupations (stage, video and audio) until performers, professional sports-men, auxiliary artistic occupations
507	102	Physicians until Pharmacists
	103	Non-medical practitioners until masseurs, physio-therapists and related occupations
	104	Nurses, midwives
	105	Nursing assistants
	106	Dietary assistants, pharmaceutical assistants until medical laboratory assistants
	107	Medical receptionists
508	108	Social workers, care workers until religious care helpers
	109	Home wardens, social work teachers
	110	Nursery teachers, child nurses
	111	University teachers, lecturers at higher technical schools and academies until technical, vocational, factory instructors
	112	Music teachers, n.e.c. until other teachers
	113	Economic and social scientists, statisticians until scientists n.e.c.
509	114	Hairdressers until other body care occupations

115	Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers until waiters, stewards
116	Others attending on guests
117	Housekeeping managers until employees by household cheque procedure
118	Laundry workers, pressers until textile cleaners, dyers and dry cleaners
119	Household cleaners until glass, buildings cleaners
120	Street cleaners, refuse disposers until machinery, container cleaners and related occupations

Note: Table shows the occupation groups. The 120 “SIAB groups” are provided in the data set. The First column denotes the 30 aggregated occupational segments (Berufsgruppen) used in the analysis.

Appendix B

Appendices to Chapter 4

B.1 Data Appendix

This appendix briefly describes the variables used for each of the data sets and lists the numbers of observations after the sample selection steps.

B.1.1 PSID

Variables

Demographic and Socioeconomic

Head and Relationship to Head. We identify *current* heads and spouses as those individuals within the family unite with `Sequence Number` equal to 1 and 2, respectively. In the PSID, the man is labelled as the household head and the woman as his spouse. Only when the household is headed by a woman alone, she is considered the head. If the family is a split-off family from a sampled family, then a new head is selected.

Age. The age variable recorded in the PSID survey does not necessarily increase by 1 from one year to the next. This may be perfectly correct, since the survey date changes every year. For example, an individual can report being 20 years old in 1990, 20 in 1991, and 22 in 1992. We thus create a consistent age variable by taking the age reported in the first year that the individual appears in the survey and add 1 to this variable in each subsequent year.

Education Level. In the PSID, the education variable is not reported every year and it is sometimes inconsistent. To deal with this problem, we use the highest education level that an individual ever reports as the education variable for each year. Since our sample contains only individuals that are at least 25 years old, this procedure does not affect our education variable in a major way.

Income

Individual Male Wages and Salaries. This is the variable used for individual income in the benchmark case. It is the answer to: *How much did (Head) earn altogether from wages or salaries in year t-1, that is, before anything was deducted for taxes or other things?* This is the most consistent earnings variable over time reported in the PSID, as it has not suffered any redefinitions or change in subcomponents[1].

Individual Male Labor Earnings. `Annual Total Labor Income` includes all income from wages and salaries, commissions, bonuses, overtime and the labor part of self-employment (farm and business income). Self-employment in PSID is split into asset and labor parts using a 50-50 rule in most cases. Because this last component has been inconsistent over time[2], we subtract the labor part of business and farm income before 1993.

Individual Female Labor Earnings. There is no corresponding `Wages and Salaries` variable for spouses. We use `Wife Total Labor Income` and follow a similar procedure as in the case of heads.

Annual Hours. For heads and wives, it is defined as the sum of annual hours worked on main job, extra jobs and overtime. It is computed using usual hours of work per week times the number of actual weeks worked in the last year.

Pre-Government Household Labor Earnings. Head and wife labor earnings.

Post-Government Household Labor Earnings. Pre-government household earnings *minus* taxes *plus* public transfers, as defined below.

Taxes. The PSID reports own estimates for total taxes until 1991. For the remaining years, we estimate taxes using TAXSIM.

Public Transfers. Transfers are considered at the family unit level, when possible. We group social and welfare programs in three broad categories. Due to changes in the PSID design, the specific definition of each program is different every year. We give an overview below and leave the specific replication details for the online Data Appendix.

Household Disposable Income. We construct this variable from Household Taxable Income (Head's and wife's income from assets, earnings, and net profit from self-employment) *minus* taxes *plus* public transfers.

[1] See Shin and Solon (2011) for a comparison of PSID male earnings variables in inequality analyses.

[2] In particular, total labor earnings included the labor parts of farm and business income up to the 1993 survey but not in subsequent waves.

Transfers

We refer to Table 4.7 in the main text for a description of the three groups of programs considered, as well as their subcomponents. In the PSID, obtaining an annual amount of each type of benefits is almost wave-specific. Every few survey years, the level of aggregation within the family unit and across welfare programs is different for at least one of our groups. To impose some common structure, we establish the following rules.

For survey years 1970-1993[3] and 2005-2011, the total annual amount of each program is reported for the head, spouse and others in the family unit. In occasions, the amount appears combined for several or all members.[4] Because in those cases it is impossible to identify separate recipiency of each member, we consider the benefit amount of the whole family. This is, we add up all available information for all family members, whether combined or separately reported.

In survey years 1994-2003, most benefits (except Food Stamps and OASDI) are reported separately for the head and the spouse only. The way amounts are reported changes as well. First, the reported amount (\$$X$) received is asked. Second, the frequency of that amount (\$$X$ per year, per month, per week, etc) is specified. We convert all amounts to a common frequency by constructing a monthly amount \$$x$ using these time values. Finally, the head and spouse are asked during which months the benefit was received. The final annual recipiency of transfers is then obtained multiplying \$$x$ by the number of months this benefit was received. For Food Stamps and OASDI, we follow the rules described for the other waves.

Detailed Sample Selection

We start with an initial sample of 584,392 SRC individuals interviewed between 1976 and 2011. We then impose the next criteria every year. The number of individuals kept at each stage in the sample selection is listed in Table I. Previous to this selection process, we have cleaned the raw data and corrected duplicates and inconsistencies (for example, zero working hours with positive labor income). We also require that the individuals have non top-coded observations in income.

1. The individual must be from the original main PSID sample (not from the Survey of Economic Opportunities or Latino subsamples).

2. In the benchmark individual sample, we select male heads of family. In the reference

[3]Our main sample refers to survey years 1977-2011, but complementary results are provided for the annual subsample of the PSID. This is, for 1970-1997. We drop the first two waves in all cases, since benefits such as OASDI, UI and WC are only reported for the family head; and benefits such as SSI are not reported at all.

[4]This is always the case for Food Stamps.

household sample, we require at least two adult members in the unit and that individuals had no significant changes in family composition. More specifically, we require that they responded either "no change" or "change in family members other than the head or wife" to the question about family composition changes.

3. The household must not have missing variables for the head or wife labor income, or for education of the head. The individuals must not have missing income or education themselves.

4. The individual must not have income observations that are outliers. An outlier is defined as being in the top 1% of the corresponding year.

5. We require the income variable of analysis to be positive.

6. Household heads must be between 25 and 65 years old.

Table B.1: Number of Observations Kept in Each Step: PSID

	Male Heads	Households	All Females
SRC	586,187	586,187	586,187
Family Composition	90,106	75,202	110,711
Non-Missing y or College	83,039	69,443	97,990
Positive Income	63,875	58,551	54,214
Outliers	63,065	57,262	53,257
Age Selection	54,593	50,102	45,330
Final #Obs for transitory changes	42,623	38,171	33,687
Final #Obs for persistent changes	34,985	30,985	27,269

Note: Table lists number of person-year, or household-year, observations in the three panels for the sample from PSID.

B.1.2 LINDA

Variables

Demographic and Socioeconomic

Head and Relationship to Head. LINDA is compiled from the Income Register based on filed tax reports and other registers. Statistics Sweden samples individuals and then adds information for all family members, where family is defined for tax purposes. This implies that there is no information about 'head of households'. We therefore define the head of a household as the sampled male.

Age. As defined by Statistics Sweden

Education Level. LINDA contains information about eduction from 1991 and onwards. An individual is assigned "college" education if it has at least 3 years of university education.

Private / Public employment An individual is defined as as working in the public sector, if he/she works in public administration, health care or education. Linda contains consistent comparable information for the years 1991 and onwards. For the years 1991-92 the public sector employment is defined as those we use SNI90 codes 72000-72003, 90000-93999 and >=96000. For 1993-2006 we use SNI92 codes 64110-64202, 73000-74110, 75000-92000, 92500-92530 and >=96000. For 2007 we use SNI2007 codes 64110-64202, 73000-74110, 75000-92000, 92500-92530 and >=96000.

Income

For the years 1985-2010 we use the measures suggested by Statistics Sweden to be comparable between years in LINDA. We construct comparable measure for the years 1979-1984.

Individual labor earnings. Labor earnings consist of wages and salaries, the part of business income reported as labor income, and taxable compensation for sick leave and parental leave.

Pre-Government Household Labor Earnings. Defined as the sum of individual labor income within the family.

Post-Government Household Labor Earnings. Post-government earnings is calculated as pre-government earnings *minus* taxes *plus* public transfers.

Household Disposable Income. Disposable income consists of the sum of factor income and minus taxes and plus public transfers.

Taxes. LINDA provides observations of total taxes paid by the individual. Since taxed paid on capital income constitute a small part of total tax payments, and since we cannot separate taxes on capital income from those on labor income, we assume that all taxes are labor income taxes.

Public Transfers. LINDA provides observations of total public transfers at the individual level (Statistics Sweden has individualized transfers given to families) and at the household level. We also consider three subcategories of transfer as listed below.

Transfers

Transfers in subcategory 1 and 3 are individual level transfers. Transfers in subcategory 2 are family level transfers but have been individualized by Statistics Sweden. For each subcategory, we take all transfers received by all members of the households.

- *HH-level transfers subcategory 1 (labor market transfers)*: sum of unemployment benefits received by all members of household.

- *HH-level transfers subcategory 2 (family aid)*: sum of transfers to support families received by all members of household.

- *HH-level transfers subcategory 3 (pensions)*: sum of old-age pensions received by all members of household.

Detailed Sample Selection

To be included in the individual sample the individual has to be sampled and between 25 and 60 years old. A family is included in the household sample if the sampled individual is a man between 25 and 60 years old and there are at least two members aged 25-60 in the family.

B.1.3 SIAB

We use the scientific use file SIAB-R7510 provided by the Institute for Employment Research (IAB). The SIAB data from which the scientific use file is constructed is a 2% random sample of all individuals covered by a dataset called IEB. This data set is from four different sources, which can be identified in the data. For construction of our sample we use earnings data stemming from BeH (employee history) and transfer data from LeH (benefit recipient history). Records in BeH are based on mandatory social security notifications from employers and hence cover individuals working in employment subject to social security, which excludes civil servants, students and self-employed. A new spell starts whenever there is a new notification, which happens when either a new employment relationship changes, an ongoing contract is changed, or with the start of a calendar year. BeH covers all workers subject to social security contributions, which excludes civil servants, self-employed and students. For details on the data set see vom Berge et al. (2013).

Variables

Demographic and Socioeconomic

Head and Relationship to Head. SIAB does not contain information on households. We use only individual level data.

Age. Birth year is reported consistently in SIAB data.

Education Level. Each individual spell in SIAB contains information on the highest degree of formal education as reported by the employer. In order to construct a consistent measure of education we apply imputation rules proposed by Fitzenberger et al. (2006).

Private / Public employment An individual is defined as as working in the public sector, if he/she works in public administration, health care or education. SIAB contains consistent comparable information for all years of the sample. We use the classification WZ93 as provided in the data, which aggregates 3 digit codes of the original WZ93 classification into 14 categories. The industry of an employer is registered once a year and assigned to the worker spells of that year. This implies that for some individual spells there is no information on the industry. For each year a worker is assigned the industry from the longest spell in that year. We classify as public employment those in sectors 13 (3-digit WZ93 801-804, 851-853: Education, social and health-care facilities) and 14 (751-753, 990: public administration, social security).

Income

Individual labor earnings. We calculate annual earnings as the sum of total earning from all valid spells for each individual. As marginal employment spells were not reported before 1999, we drop marginal employment in the years where they are reported to obtain a time consistent measure. For the same reason we drop spells with reported average daily wage rate below the highest marginal employment threshold in the sample period, which is 14.15 Euros (in 2003 Euros). There are two drawbacks in the available data: structural break of the wage measure in 1984 and top-coding.

Structural break in wage measure Since 1984 the reported average daily wage rate from an employment spell includes one-time payments. We correct for this structural break following a procedure based on Dustmann et al. (2009): we rank individuals from 1976 to 1983 into 50 quintiles of the annual full-time wage distributions. Then we fit locally weighted regressions of the wage growth rate from 1982-1983 on the quintiles in 1983 and the same for 1983-1984. We then define as the correction factor the difference between the quintile-specific smoothed value of wage growth between 1984 and 1983. The underlying assumption is that wage growth should be higher from 1983-1984 because the wage measure includes one-time payments. In order to control for overall wage growth differences we subtract the average of the correction factor of the second to 20th quintiles. The resulting percentile-specific correction factor is then applied to wages in 1976-1983.

Imputation of top-coded wages Before aggregating earnings from all spells we correct full-time wage spells for the top-coding. We therefore follow Daly et al. (2014) and fit a Pareto tail to the cross-sectional wage distribution. The Pareto distribution is estimated separately for each year by age-group and sex. We define seven age groups: 25-29,30-34,...,55-60. As starting point for the Pareto we choose the 60th percentile of the subgroup-specific distribution. As in Daly et al. (2014), we draw one random number by individual which we then apply to the annual specific distributions when assigning a wage to the top-coded workers. We apply the imputation method to the annual distribution of average full-time wages and hence an individual can be below the cutoff limit if, e.g., from two full-time spells in a year only one is top-coded. We therefore define as top-coding limit the annual specific limit minus 3 DM (1995 DM) as in Dustmann et al. (2009).

Transfers

In SIAB we observe consistently over time unemployment benefits at the individual level.

Detailed Sample Selection

To be included in the sample the individual has to be between 25 and 60 years old and earn a gross income above 520*0.5*minimum wage. We drop all workers which have at least one spell reported in East Germany.

B.1.4 SOEP

Variables

Demographic and Socioeconomic

Head and Relationship to Head. For each individual in the sample, SOEP reports the relationship to the head of household in any given wave. Whenever there is a non-couple household, i.e., no spouse is reported, the reported head is classified as head. Whenever we observe a couple household and the reported head is a male we keep this; when the reported head is a female and the reported spouse is a male, we reclassify the male to be head and the female to be spouse.

Age. The age is measured by subtracting year of birth from the current year.

Education Level. The education variable used categorizes the obtained maximum education level by ISCED 1997. An individual with category 6 is assigned "college" education, an individual with categories 1-5 is assigned "non-college". Category 6 includes a degree obtained from university, from technical college, from a university abroad, and a PhD. An individual still in school (category 0) is assigned a missing. For a small number of individuals the described procedure yields inconsistencies in the sense that for some year t the assignment is "college" and some later year t+s the assignment is "non-college"; in these cases we assign "college" to the later year.

Income and Hours

Individual labor income. Labor earnings are calculated from individual labor income components and includes income from first job, secondary job, 13th and 14th salary, christmas bonus, holiday bonus, profit sharing. For consistency with the PSID measure we assign 50% of income from self-employment to labor income.

Household level labor income. Defined as the sum of individual labor income of head and spouse.

Annual Hours. SOEP measures the average actual weekly hours worked and the numbers of months an individual worked. From these measures SOEP provides a constructed measure of annual hours worked of an individual.

Pre-Government Household Labor Earnings. Head and spouse labor earnings.

Post-Government Household Labor Earnings. Pre-government household earnings *minus* taxes *plus* public transfers, as defined below.

Taxes. SOEP provides estimates of total taxes at the household level.

Public Transfers. Transfers are considered at the family unit level and at the individual level. We group social and welfare programs in three broad categories as listed below.

Household Disposable Income. We construct this variable from Household Taxable Income (Head's and wife's income from assets, earnings, and net profit from self-employment) *minus* taxes *plus* public transfers. SOEP provides a measure of household asset flows, which is calculated as income from renting minus operating costs, plus dividend income.

Transfers

Transfers are partly observed at the individual level and partly at the household level. For each subcategory, we take all transfers received by all members of the households.

- *HH-level transfers*: we use transfers received by all individual household members in order to calculate measures that are consistent over time. For each individual, total transfers are the sum of the following components: old-age pensions, widow's pensions, maternity benefit, student grants, unemployment benefits, subsistence allowance, unemployment assistance (up to 2004); at the hh-level we measure received child allowances and the total unemployment benefits II received by all household members (since 2005 replacing unemployment assistance).

- *HH-level transfers subcategory 1 (labor market transfers)*: sum of unemployment benefits received by all members of household.

- *HH-level transfers subcategory 2 (family aid)*: sum of subsistence allowance of all members, + sum of unemployment assistance received by all members (up to 2004), + hh-level measure of unemployment benefits II (since 2005).

- *HH-level transfers subcategory 3 (pensions)*: sum of old-age pensions received by all members of household.

Sample Selection

In order to be in the initial sample for a year, the individual or household head must be between ages 25 and 60 and live in West Germany. In order to have a consistent sample, we drop the immigrant subsample and the high income subsample. This gives initial sample sizes of 87,582 individual-year observations for the male sample, 76,249 individual-year observations for the female sample, and 76,051 household-year observations for the household sample. The sample selection then follows the steps listed below for each sample. All cross-sectional statistics are calculated using appropriate cross-sectional individual or household weights, respectively.

1. drop if no info on education or if no degree obtained yet
2. drop if currently working in military
3. drop if no info on income
4. drop if no info on hours worked
5. keep if income > 0 and hours > 520
6. drop if in highest percentile (sample outliers)
7. drop if below 520*0.5**minimum wage*, where *minimum wage* is set to be 6€ in year 2000 Euros
8. for transitory change measure: keep if in sample in t and t-1
9. for permanent change measure: keep if in sample in t and t-5

Table B.2: Number of Observations Kept in Each Step: SOEP

selection step	Male Heads	Households	All Females
initial	87,582	76,051	76,249
drop if no coll. info	86,737	75,310	75,270
drop if in military	86,712	75,293	75,268
drop if no obs on ymin	79,547	75,070	50,374
drop if no obs on hours	79,547	75,070	50,374
keep if >=520 hrs and ymin>0	77,265	71,389	42,245
drop top 1% of ymin per year	76,404	70,627	41,830
drop if ymin<.5*520*min wage	76,268	70,097	41,434
Final #Obs for transitory changes	64,572	59,209	31,612
Final #Obs for persistent changes	38,399	34,792	16,792

Note: Table lists number of person-year, or household-year, observations in the three panels for the sample from SOEP.

B.2 Cyclicality of Individual Earnings by Groups

Tables B.3 to B.8 show results of the individual level earnings regressions discussed in Chapter 4.4 by subgroups.

Table B.3: Cyclicality of Male Earnings, by Education Groups

	L9010	Kelley	L9050	L5010
	United States			
College Graduates	0.25	0.58*	0.35*	–0.10
	(0.90)	(1.97)	(1.98)	(–0.64)
Non-College	–0.38	1.84***	0.52*	–0.90***
	(–0.84)	(4.17)	(1.83)	(–3.19)
	Sweden			
College Graduates	–0.00	1.80***	0.42	–0.42***
	(–0.01)	(4.93)	(1.58)	(–5.72)
Non-College	–0.17	4.03***	0.99***	–1.26***
	(–1.52)	(3.86)	(3.39)	(–3.53)
	Germany (SIAB)			
College Graduates	0.62	4.70***	1.24**	–0.61**
	(1.01)	(3.10)	(2.17)	(–2.29)
Non-College	0.10	5.26***	0.89***	–0.79***
	(0.25)	(5.41)	(3.07)	(–3.78)

Note: See Table 4.2 for explanations.

Table B.4: Cyclicality of Female Earnings, by Education Groups

	L9010	Kelley	L9050	L5010
	United States			
College graduates	–0.60	1.08*	0.18	–0.78**
	(–1.70)	(1.77)	(0.57)	(–2.50)
Non-college	0.79***	0.59	0.67***	0.12
	(3.59)	(1.46)	(3.14)	(0.53)
	Sweden			
College graduates	0.13	1.15***	0.64	–0.25
	(0.31)	(4.03)	(1.22)	(–1.74)
Non-college	0.50*	1.81***	0.75***	–0.25**
	(1.96)	(3.40)	(2.78)	(–2.71)
	Germany (SIAB)			
College graduates	0.01	2.03	1.01	–1.00
	(0.01)	(1.65)	(1.12)	(–1.39)
Non-college	0.32	2.58**	0.77	–0.45*
	(0.47)	(2.08)	(1.27)	(–1.88)

Note: See Table 4.2 for explanations.

Table B.5: Cyclicality of Individual Earnings, by Sector of Employment, Males

	L9010	Kelley	L9050	L5010
	Sweden			
Private	0.10	3.83***	0.93***	–0.83***
	(0.93)	(4.02)	(3.81)	(–4.08)
Public	–0.45***	2.10***	0.17	–0.62***
	(–3.93)	(6.55)	(1.64)	(–9.11)
	Germany			
Private	0.03	5.55***	0.88***	-0.85***
	(0.08)	(6.44)	(3.55)	(–5.64)
Public	2.50	0.30	1.45	1.06
	(1.16)	(0.17)	(1.08)	(1.01)

Note: See Table 4.2 for explanations.

Table B.6: Cyclicality of Individual Earnings, by Sector of Employment, Females

	L9010	Kelley	L9050	L5010
	Sweden			
Private	0.50*	1.99***	0.78**	–0.29**
	(1.87)	(3.02)	(2.81)	(–2.43)
Public	0.18	1.10***	0.34**	–0.16**
	(1.19)	(3.29)	(2.43)	(–2.61)
	Germany			
Private	0.01	3.13**	0.73	–0.72***
	(0.01)	(2.44)	(1.50)	(–3.15)
Public	1.17	0.95	0.85	0.32
	(0.84)	(0.68)	(0.85)	(0.59)

Note: See Table 4.2 for explanations.

Table B.7: Cyclicality of Individual Earnings, by Occupational Segments, Males; Germany (SIAB)

	L9010	Kelley	L9050	L5010
	Distribution of Beta Coefficients			
Mean	0.71	8.78	2.06	-1.35
P10	-0.83	3.68	0.90	-2.91
Median	0.46	8.35	1.75	-1.29
P90	2.62	13.09	3.29	-0.18
Standard Deviation	1.30	3.52	1.37	1.47
Min	-1.55	2.36	0.66	-7.09
Max	4.56	17.87	7.89	1.30
	Distribution of t-Statistics			
Mean	0.34	4.11	2.59	-2.21
P10	-0.90	1.39	1.43	-4.93
Median	0.46	3.23	2.46	-2.22
P90	1.19	7.73	3.73	-0.18
Standard Deviation	0.87	2.71	1.07	1.79
Min	-2.30	1.01	0.99	-6.62
Max	2.01	11.46	6.36	0.72

Note: The table displays moments of the distribution of beta-coefficients (upper panel) and t-statistics (lower panel) from separate regressions for each of the 30 occupational segments. See notes for Table 4.2.

Table B.8: Cyclicality of Individual Earnings by Occupational Segments, Females; Germany (SIAB)

	L9010	Kelley	L9050	L5010
	Distribution of Beta Coefficients			
Mean	-0.10	6.87	1.98	-2.08
P10	-3.33	0.96	0.89	-4.45
Median	0.12	6.30	2.06	-2.00
P90	1.97	12.26	3.10	0.69
Standard Deviation	2.25	3.94	1.37	1.96
Min	-6.40	-0.56	-4.13	-7.20
Max	3.61	13.50	3.80	0.84
	Distribution of t-Statistics			
Mean	-0.11	2.35	1.43	-1.84
P10	-1.53	0.31	0.53	-4.28
Median	0.05	1.81	1.38	-1.35
P90	0.71	5.41	2.27	0.52
Standard Deviation	0.80	1.81	0.89	1.73
Min	-2.06	-0.07	-0.72	-6.30
Max	0.95	6.15	4.04	0.61

Note: The table displays moments of the distribution of beta-coefficients (upper panel) and t-statistics (lower panel) from separate regressions for each of the 30 occupational segments. See notes for Table 4.2.

B.3 Robustness of the Empirical Results

We perform a number of robustness checks for the analyses based on SIAB data, which deal with (i) top-coding of incomes and (ii) a structural break in the income measure in 1984. In addition to Kelley's skewness we consider two alternatives-2 versions of Hinkley's measure of skewness. Instead of L9050 and L5010, these measures relate L8550 and L5015 or L8050 and L5020, respectively.

The first four rows of table B.9 show the results of the regressions for male and female earnings wages, respectively. The results are the ones from the main text and serve for comparison to the robustness analyses. Columns 7-12 show the results for the two versions of Hinkley's skewness measures and the corresponding tails. Compared to Kelley's skewness and L9050 and L5010, the estimates show that the substantive conclusion is robust also for these smaller log percentile differentials. Rows 5 and 6 show the results for the wage regressions when applying a less strict criterion of working full-time for only 45 weeks in two consecutive years. Again, the results are as the reported ones for 50 weeks.

In order to ensure that top-coding does not drive our results, we redo the analysis using reduced samples in which an individual is considered in the distribution of income changes from t to t+1 only if income is below the top-coding thresholds in both t and t+1. About 11% and 2% of all observations are top-coded in the male and female base samples, respectively. Table B.10 shows the results of the respective regressions for earnings, wages, and wages of firm stayers for both males and females. Second, we rerun the regressions completely ignoring top-coding, i.e., all individuals from the base sample are in the sample - but with their reported incomes again for earnings, wages, and wages of stayers. Results are table B.11.

A rerun of the regression analysis using only observations after 1983, thereby dropping all years for which the reported income measure does not include one-time payments such as bonuses, does not change the results (lower panel of table B.11).

Table B.9: Sensitivity of Regression Results - SIAB I

	Std Dev	L9010	Skew	Kelley	L9050	L5010	Hinkley 1	Hinkley 2	L8550	L8050	L5015	L5020
Male Earnings	0.07	0.15	14.42***	5.48***	0.95***	-0.80***	5.84***	5.85***	0.51***	0.32***	-0.54***	-0.36***
	(0.42)	(0.36)	(4.28)	(5.80)	(3.14)	(-4.11)	(9.85)	(7.51)	(4.10)	(3.57)	(-4.77)	(-3.43)
Female Earnings	0.10	0.34	4.34*	2.55**	0.80	-0.46*	2.75**	2.71***	0.43	0.25	-0.24**	-0.14*
	(0.47)	(0.48)	(1.77)	(2.05)	(1.25)	(-1.80)	(2.62)	(3.85)	(1.40)	(1.65)	(-2.56)	(-1.87)
Male Wages	0.01	-0.09	14.55***	4.73***	0.30***	-0.39***	4.94***	4.88***	0.22**	0.18**	-0.28**	-0.20**
	(0.23)	(-0.54)	(4.58)	(6.31)	(3.77)	(-3.20)	(4.35)	(3.37)	(2.59)	(2.66)	(-2.55)	(-2.07)
Female Wages	0.04	0.03	8.98*	2.12***	0.17**	-0.14	2.20***	2.09***	0.14**	0.11**	-0.09	-0.04
	(0.66)	(0.18)	(2.02)	(5.11)	(2.61)	(-1.58)	(4.79)	(4.67)	(2.68)	(2.65)	(-1.24)	(-0.83)
Male Wages	0.01	-0.08	13.20***	4.65***	0.31***	-0.39***	4.88***	4.85***	0.23**	0.18***	-0.29**	-0.20**
(45 weeks)	(0.27)	(-0.54)	(4.55)	(6.60)	(3.90)	(-3.30)	(4.50)	(3.48)	(2.70)	(2.78)	(-2.61)	(-2.09)
Female Wages	0.04	0.04	8.80*	2.07***	0.17**	-0.14	2.20***	2.10***	0.14**	0.12**	-0.09	-0.05
(45 weeks)	(0.72)	(0.25)	(2.02)	(5.21)	(2.72)	(-1.57)	(4.85)	(4.72)	(2.73)	(2.66)	(-1.23)	(-0.84)

Note: See notes for Table 4.2.

Table B.10: Sensitivity of Regression Results - SIAB II

	Std Dev	L9010	Skew	Kelley	L9050	L5010	Hinkley 1	Hinkley 2	L8550	L8050	L5015	L5020
	Not top-coded workers only:											
Male Earnings	0.08	0.26	14.49***	4.98***	0.96**	-0.70***	4.83***	4.65***	0.48***	0.31***	-0.44***	-0.28***
	(0.41)	(0.53)	(4.26)	(4.28)	(2.53)	(-3.07)	(6.66)	(8.86)	(3.13)	(3.40)	(-4.06)	(-3.08)
Male Wages	-0.01	-0.05	8.76***	3.39***	0.23***	-0.28***	3.49***	3.36***	0.19***	0.14***	-0.20**	-0.14*
	(-0.14)	(-0.29)	(6.07)	(10.76)	(3.52)	(-2.91)	(8.43)	(8.09)	(3.74)	(3.49)	(-2.34)	(-2.00)
Male Wages	-0.03	-0.08	11.41***	3.66***	0.22***	-0.30***	3.67***	3.48***	0.17***	0.13***	-0.21**	-0.14**
(stayers)	(-0.75)	(-0.52)	(5.77)	(9.09)	(4.12)	(-2.96)	(7.52)	(7.65)	(4.14)	(3.63)	(-2.42)	(-2.10)
Female Earnings	0.09	0.33	4.67*	2.54*	0.80	-0.46*	2.72**	2.67***	0.43	0.25	-0.23**	-0.13*
	(0.45)	(0.47)	(1.90)	(2.03)	(1.24)	(-1.83)	(2.57)	(3.76)	(1.40)	(1.67)	(-2.46)	(-1.71)
Female Wages	0.04	0.05	2.04	2.05***	0.17**	-0.12	2.11***	2.12***	0.13***	0.11**	-0.08	-0.05
	(0.71)	(0.31)	(0.66)	(4.42)	(2.64)	(-1.34)	(4.10)	(4.56)	(2.77)	(2.74)	(-1.08)	(-0.92)
Female Wages	0.02	0.03	3.87	2.17***	0.16***	-0.12	2.25***	2.18***	0.13***	0.10***	-0.08	-0.05
(stayers)	(0.56)	(0.25)	(0.78)	(4.11)	(3.16)	(-1.38)	(4.04)	(4.46)	(3.24)	(2.99)	(-1.15)	(-0.98)

Note: See notes for Table 4.2.

Table B.11: Sensitivity of Regression Results - SIAB III

	Std Dev	L9010	Skew	Kelley	L9050	L5010	Hinkley 1	Hinkley 2	L8550	L8050	L5015	L5020
	Ignore Top-Coding:											
Male Earnings	0.07	0.15	14.72***	5.68***	0.91***	-0.76***	5.97***	6.17***	0.48***	0.30***	-0.52***	-0.37***
	(0.40)	(0.40)	(4.30)	(5.70)	(3.14)	(-4.68)	(10.66)	(8.02)	(4.27)	(3.46)	(-5.60)	(-4.51)
Male Wages	-0.01	-0.09	13.36***	4.93***	0.29***	-0.38***	5.40***	5.38***	0.21**	0.15*	-0.30***	-0.22***
	(-0.27)	(-0.69)	(4.24)	(7.59)	(4.59)	(-3.86)	(5.11)	(3.76)	(2.57)	(1.95)	(-3.59)	(-3.22)
Male Wages	-0.04	-0.13	16.06***	5.19***	0.27***	-0.39***	5.55***	5.36***	0.19**	0.14*	-0.31***	-0.22***
(stayers)	(-1.15)	(-1.06)	(3.47)	(6.67)	(4.03)	(-3.85)	(4.63)	(3.51)	(2.11)	(1.85)	(-3.58)	(-3.17)
Female Earnings	0.10	0.34	4.36*	2.51*	0.79	-0.45*	2.70**	2.63***	0.41	0.24	-0.23**	-0.13*
	(0.48)	(0.48)	(1.76)	(2.02)	(1.24)	(-1.78)	(2.61)	(3.98)	(1.39)	(1.65)	(-2.55)	(-1.84)
Female Wages	0.03	0.02	1.91	2.03***	0.15**	-0.13	2.16***	2.17***	0.13**	0.11**	-0.09	-0.05
	(0.65)	(0.16)	(0.60)	(4.79)	(2.64)	(-1.51)	(4.68)	(5.10)	(2.74)	(2.68)	(-1.29)	(-1.11)
Female Wages	0.02	0.01	3.52	2.20***	0.14***	-0.13	2.35***	2.27***	0.12***	0.10***	-0.09	-0.05
(stayers)	(0.48)	(0.09)	(0.75)	(4.45)	(3.31)	(-1.58)	(4.70)	(4.90)	(3.30)	(3.01)	(-1.40)	(-1.18)
	1984-2010:											
Male Earnings	-0.04	-0.07	13.25***	5.10***	0.81***	-0.88***	5.82***	6.22***	0.46***	0.31***	-0.61***	-0.42***
	(-0.26)	(-0.18)	(3.84)	(5.85)	(2.96)	(-3.99)	(11.04)	(9.21)	(3.83)	(3.12)	(-5.48)	(-4.33)
Female Earnings	0.04	0.30	3.86	2.46*	0.75	-0.46	2.79**	2.88***	0.42	0.26	-0.26**	-0.16*
	(0.21)	(0.39)	(1.51)	(1.84)	(1.10)	(-1.65)	(2.46)	(3.65)	(1.24)	(1.49)	(-2.29)	(-1.87)

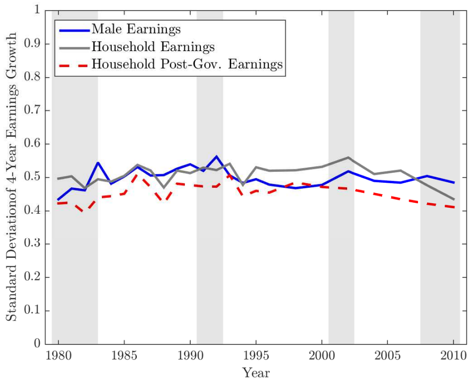
Note: See notes for Table 4.2.

B.4 Long-Run Earnings Growth

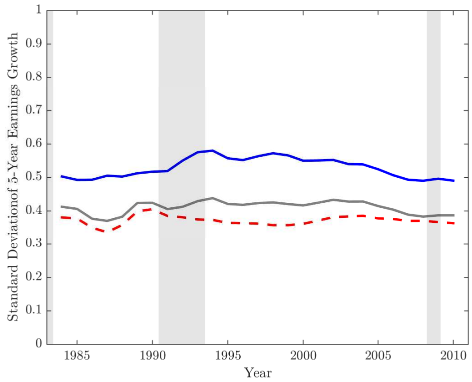
Figures B.1 to B.3 characterize the distribution of long-run earnings growth, i.e., five-year changes for Germany and Sweden, and four-year changes for the United States

Figure B.1: Standard Deviation of Long-Run Earnings Growth: United States, Germany, and Sweden

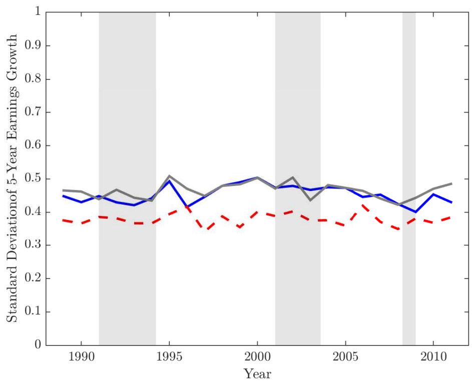
(a) United States



(b) Sweden

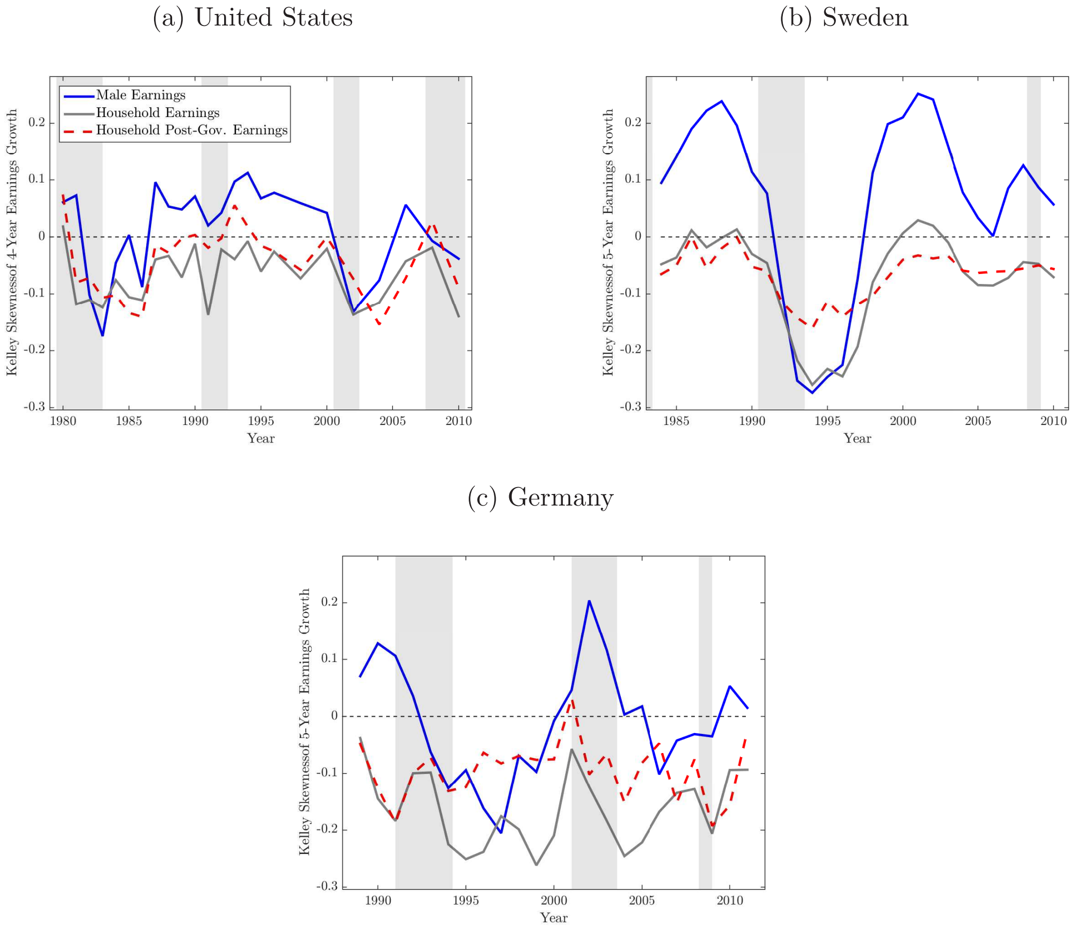


(c) Germany



Note: Linear trend removed, centered at sample average.

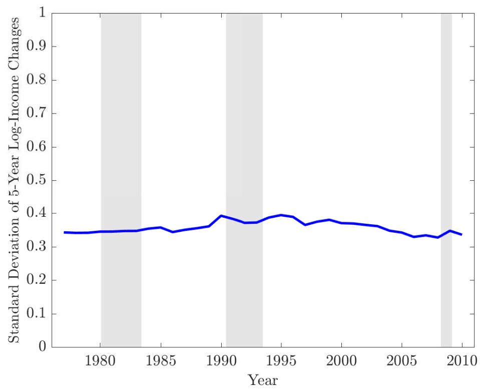
Figure B.2: Kelley Skewness of Long-Run Earnings Growth: United States, Germany, and Sweden



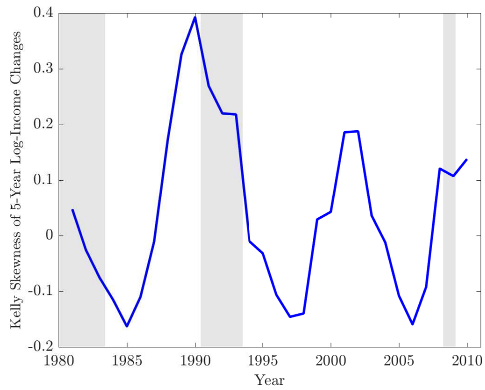
Note: Linear trend removed, centered at sample average.

Figure B.3: Standard Deviation, Skewness, and Tails of Long-Run Earnings Growth: Germany, IAB Sample

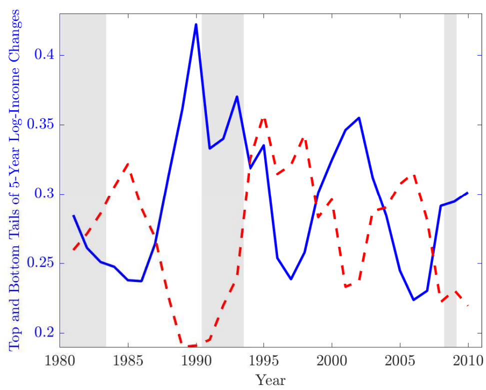
(a) Standard Deviation: Males



(b) Kelley Skewness: Males



(c) Upper and Lower Tails: Males



Note: Linear trend removed, centered at sample average.

B.5 Details on the Estimation and Simulation

Parametric Specification

Let Y_t denote household earnings in period t, and define $y_t \equiv \log Y_t$. We assume y_t evolves according to the following process:

$$\begin{aligned} y_t &= z_t + \theta_t \\ z_t &= z_{t-1} + \zeta_t \end{aligned} \tag{B.1}$$

where ε_t is an *iid* transitory shock with distribution $\mathcal{N}(\mu_\theta, \sigma_\theta)$,[5] and ζ_t denotes a permanent shock with time-varying and business-cycle dependent distribution. In particular, ζ_t follows a mixture of three normals:

$$\zeta_t \sim \begin{cases} \mathcal{N}(\mu_{1t,}, \sigma_1) & \text{with probability } p_1 \\ \mathcal{N}(\mu_{2t}, \sigma_2) & \text{with probability } p_2 \\ \mathcal{N}(\mu_{3t}, \sigma_3) & \text{with probability } p_3 \end{cases} \tag{B.2}$$

where $\sum_{j=1}^{3} p_j = 1$.

We follow McKay (2016) and incorporate the dynamics of aggregate risk in the stochastic component of household earnings, as opposed to imposing discrete events for recessions and expansions. Namely, the time-varying means are specified as:

$$\begin{aligned} \mu_{1t} &= \bar{\mu}_t \\ \mu_{2t} &= \bar{\mu}_t + \mu_2 - \phi x_t \\ \mu_{3t} &= \bar{\mu}_t + \mu_3 - \phi x_t \end{aligned} \tag{B.3}$$

where $\bar{\mu}_t$ is a normalization such that $E(e^{\zeta_t}) = 1$ for all t, and $x_t \equiv -(\log \frac{GDP_{t+1}}{GDP_t})$ captures the business cycle.[6] We use GDP growth as the empirical measure of aggregate fluctuations in order to make the quantitative results easily interpretable in relation to the empirical estimates shown in section 4.4. The parameter ϕ determines how much of aggregate risk is transmitted to idiosyncratic earnings risk and will be estimated alongside the other parameters that drive the distributions of the shocks.

Notice that business-cycle risk is transmitted to household earnings only through the permanent shock. Blundell et al. (2016), among others, concluded that transitory shocks are almost entirely insurable by the household. That is, transitory shocks barely affect

[5] μ_θ is chosen such that $\mathbb{E}\left(e^\theta\right) = 1$.

[6] To be precise, in the estimation we standardize log GDP changes.

consumption decisions or welfare. Therefore, we refrain from unnecessarily complicating our model and leave the transitory shock as in the standard case.

The vector of parameters left to be estimated is:

$$\theta \quad = \quad (\sigma_\theta, p_1, \mu_2, \mu_3, \sigma_1, \sigma_2, \phi)$$

Estimation

We estimate θ by Method of Simulated Moments (MSM). We target the time series of the 10th, 50th, and 90th percentiles of the 1, 3, and 5-year earnings changes distribution, as well as the age profile of the cross-sectional variance from age 25 to 60. In the case of the United States, we target the 2, 4, and 6-year changes. For ease of notation, we will describe our methodology taking Sweden and Germany as reference; the adaptation to the US case is trivial. The total number of moments varies by country. The specific number in each case is included in table B.12.

To construct the simulated income profiles over time, we write earnings growth as a function of the shocks, using equation (B.1):

$$y_{t+\tau} - y_t \quad = \quad \theta_{t+\tau} - \theta_t + \sum_{j=1}^{\tau} \zeta_{t+j}, \tag{B.4}$$

for the different horizons $\tau = 1, 3, 5$.

The simulated series of the life-cycle variance profile of log earnings is computed as follows. We assume a time-invariant distribution of shocks by imposing $x_t \equiv 0$ in equation (B.3). Notice that this assumes that the variance accumulates linearly over the life cycle. We then normalize the series so that the variance at age 25 in the simulation is 0. Finally, we rescale the resulting simulated profile to have the mean of its empirical counterpart.

We simulate these profiles $R = 10$ times and compute the moments corresponding to the aforementioned targets. To find $\hat{\theta}$, we next minimize the average scaled distance between the simulated and empirical moments. A weighting matrix is used to scale the life-cycle profile. In particular, we weight the variance profile with 0.2 and the remaining moments with 0.8. For the optimization part, we use a global version of the Nelder-Mead algorithm with several quasi-random restarts, as described in Guvenen (2011).

Simulation of Income Profiles

Let c_n^m denote the empirical moment n ($n = 1, \cdots, N$) that corresponds to cross-sectional target m, where

$$m \in \{p10(\Delta^1 y_t), p10(\Delta^3 y_t), p10(\Delta^5 y_t), \cdots, var(y_{age=25}), ..., var(y_{age=60})\}.$$

In each simulation, we draw a vector of random variables

$$X_r = \{\varepsilon_1, \varepsilon_2, ..., \varepsilon_{T-1}, \varepsilon_T, \zeta_1, \zeta_2, ..., \zeta_{T-1}, \zeta_T\},$$

where T denotes the last year available in the data in levels. We simulate these profiles $R = 10$ times. In order to accommodate the mean shift of the distribution of earnings changes over time, we shift the simulated earnings changes such that the mean of the 1 year earnings changes fits the data.[7]

Optimization

We minimize the scaled deviation $F(\theta)$ between each data and simulated moment.

$$min_\theta F(\theta)' W F(\theta),$$

where F is defined as:

$$\begin{aligned} F_n(\theta) &= \frac{d_n^m(\theta) - c_n^m}{|c_n^m| + \gamma^m} \\ d_n^m(\theta) &= \frac{1}{R} \sum_{r=1}^{R} d_n^m(\theta, X_r) \end{aligned}$$

Notice that the scaling can be problematic in the case of the P50 and the mean, which are very close to zero. γ^m is chosen such that, for those two moments, the denominator is, on average, equal to the sample average of the P90 moment. The average is calculated within the same group m. This is,

[7]For the US, we use the annual waves of the PSID to calculate the 1-year changes mean for the period 1976-1996. For the remaining of the sample, we annualized the biennial changes.

$$
\begin{aligned}
\gamma^m &= \tfrac{1}{T-1}\left[\sum_{i=1}^{T-1}|c_n^{p90,1}| - \sum_{i=1}^{T-1}|c_n^m|\right] \quad for \quad m \in \{p50(\Delta^1 y_t)\} \\
\gamma^m &= \tfrac{1}{T-3}\left[\sum_{i=1}^{T-3}|c_n^{p90,3}| - \sum_{i=1}^{T-3}|c_n^m|\right] \quad for \quad m \in \{p50(\Delta^3 y_t)\} \\
\gamma^m &= \tfrac{1}{T-5}\left[\sum_{i=1}^{T-5}|c_n^{p90,5}| - \sum_{i=1}^{T-5}|c_n^m|\right] \quad for \quad m \in \{p50(\Delta^5 y_t)\}
\end{aligned}
$$

and $\gamma^m = 0$ otherwise.

Because our goal is to capture as closely as possible the business cycle fluctuations of idiosyncratic income risk, we impose the mean of the medium-run income changes to be as in the data. We adjust the weighting matrix such that the cross-sectional moments get a weight of 80% and the life cycle moments get a weight of 20%.

Parameter Estimates and Model Fit

As noted at the beginning of this section, we estimate income processes for pre-government household labor income and, separately, for post-government household income. Tables B.13a and B.13b show the parameter estimates for the three economies under both scenarios. For each country and income measue, figures B.4 to B.9 show the empirical moments and the simulated moments implied by the estimated paramters.

Table B.12: Estimated parameter values

Parameter	Description	Value		
		US	Sweden	Germany
p_1	Weight of center of ζ distribution	0.9711	0.9628	0.9388
p_2	Weight of right tail of ζ distribution	0.0144	0.0186	0.0306
p_3	Weight of left tail of ζ distribution	0.0144	0.0186	0.0306
σ_ε	St. dev. of transitory income shock	0.2101	0.1048	0.1501
$\sigma_{1,\zeta}$	St. dev. of center of ζ distribution	0.1077	0.0872	0.0785
$\sigma_{2,\zeta}$	St. dev. of right tail of ζ distribution	0.0343	0.0079	0.0016
$\sigma_{3,\zeta}$	St. dev. of left tail of ζ distribution	0.0343	0.0079	0.0016
μ_2	Mean of right tail of ζ distribution	0.1380	0.0940	0.0000
μ_3	Mean of left tail of ζ distribution	-0.0000	-0.0000	-0.4125
ϕ	Aggregate risk transmission parameter	0.5738	0.5968	0.4045
M	# moments targeted in estimation	252	297	261

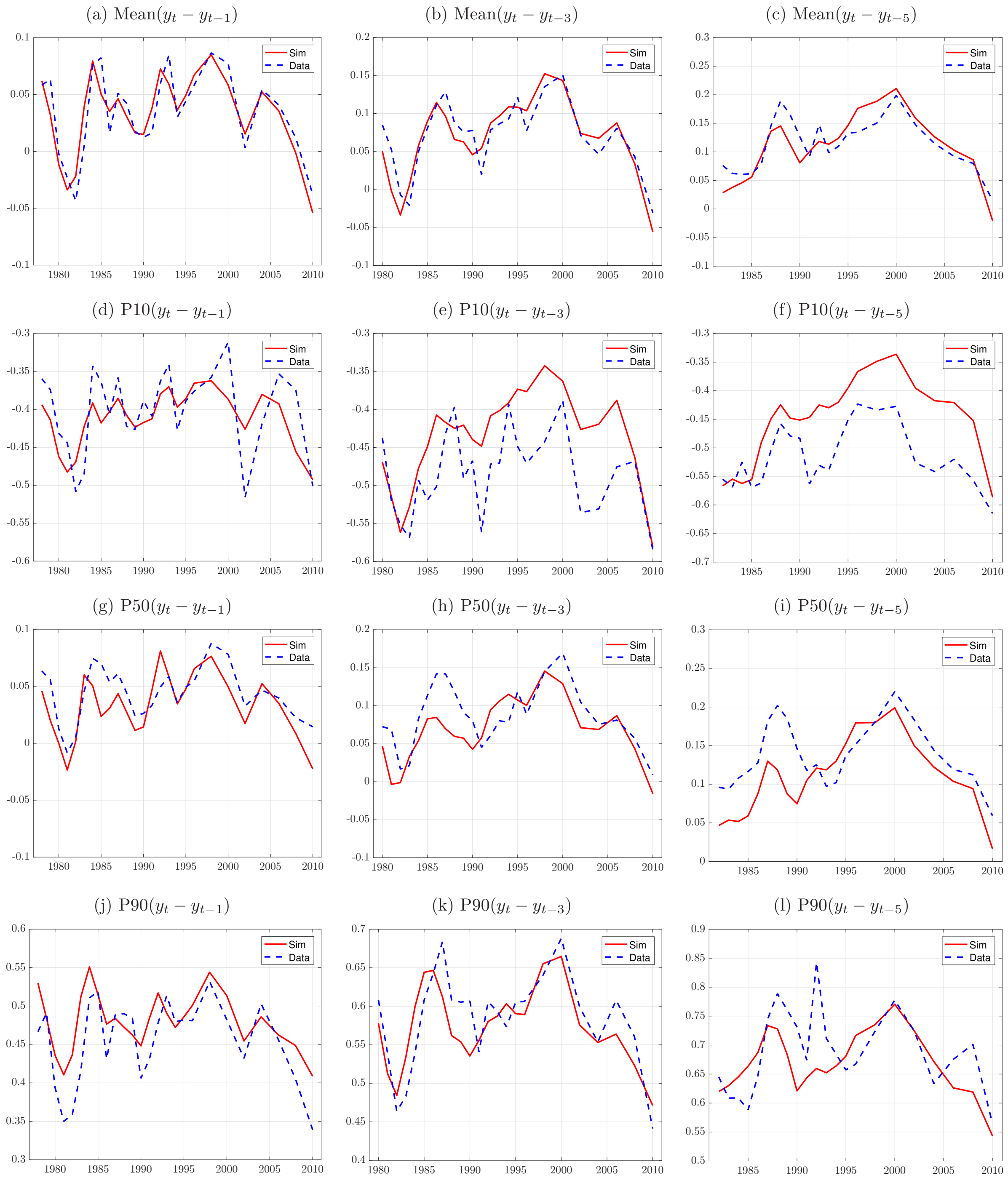
(a) Pre-Government Earnings

Parameter	Description	Value		
		US	Sweden	Germany
p_1	Weight of center of ζ distribution	0.9765	0.9434	0.9294
p_2	Weight of right tail of ζ distribution	0.0118	0.0283	0.0353
p_3	Weight of left tail of ζ distribution	0.0118	0.0283	0.0353
σ_ε	St. dev. of transitory income shock	0.1921	0.0869	0.1385
$\sigma_{1,\zeta}$	St. dev. of center of ζ distribution	0.0902	0.0452	0.0523
$\sigma_{2,\zeta}$	St. dev. of right tail of ζ distribution	0.0113	0.0007	0.0000
$\sigma_{3,\zeta}$	St. dev. of left tail of ζ distribution	0.0113	0.0007	0.0000
μ_2	Mean of right tail of ζ distribution	0.2313	0.1002	0.0000
μ_3	Mean of left tail of ζ distribution	-0.0000	-0.0000	-0.1526
ϕ	Aggregate risk transmission parameter	0.3893	0.3231	0.3131
M	# moments targeted in estimation	252	297	261

(b) Post-Government Earnings.

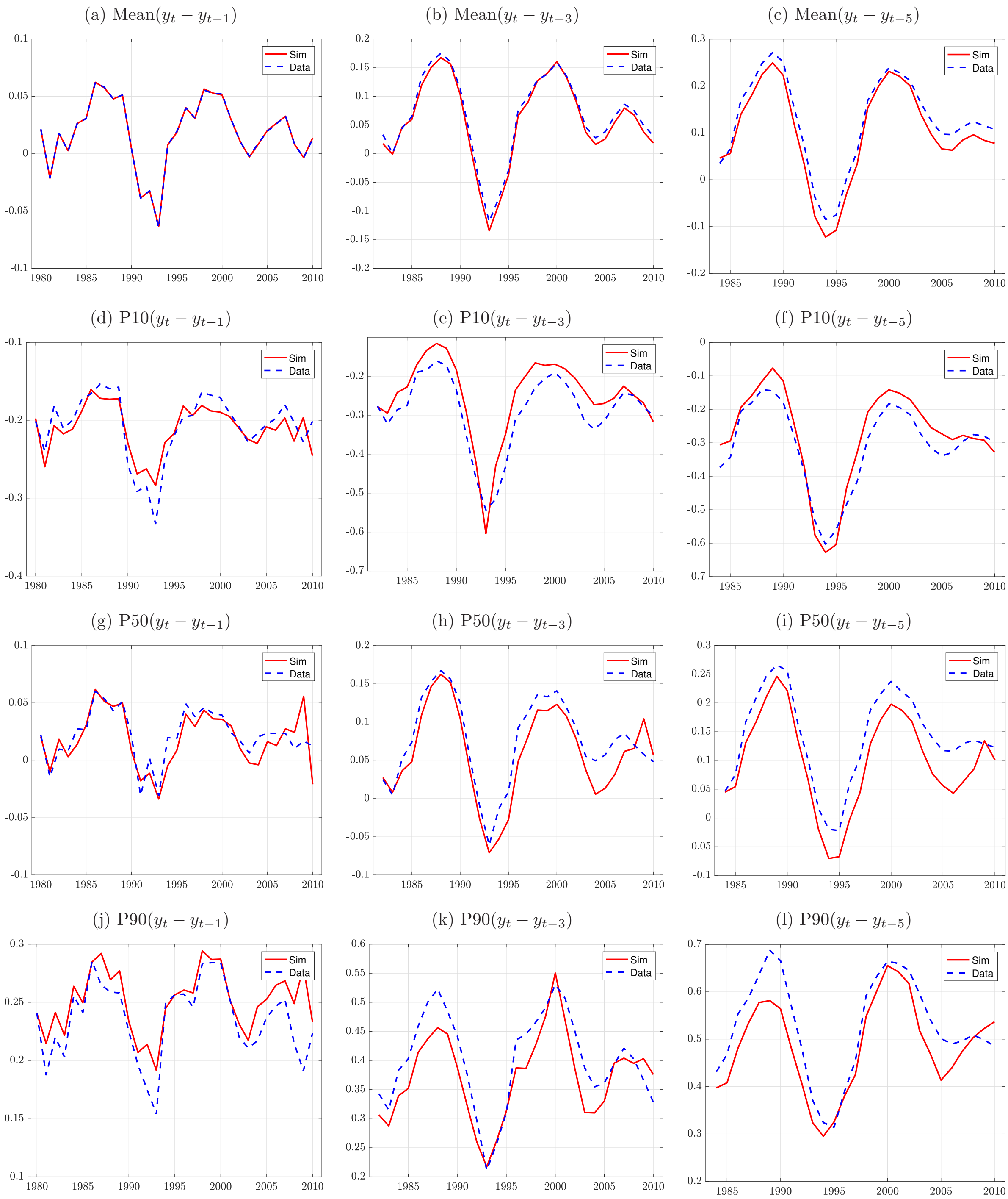
Note: Estimated parameters for the different countries and income variables. For details o

Figure B.4: Pre-Government Income Fit: United States



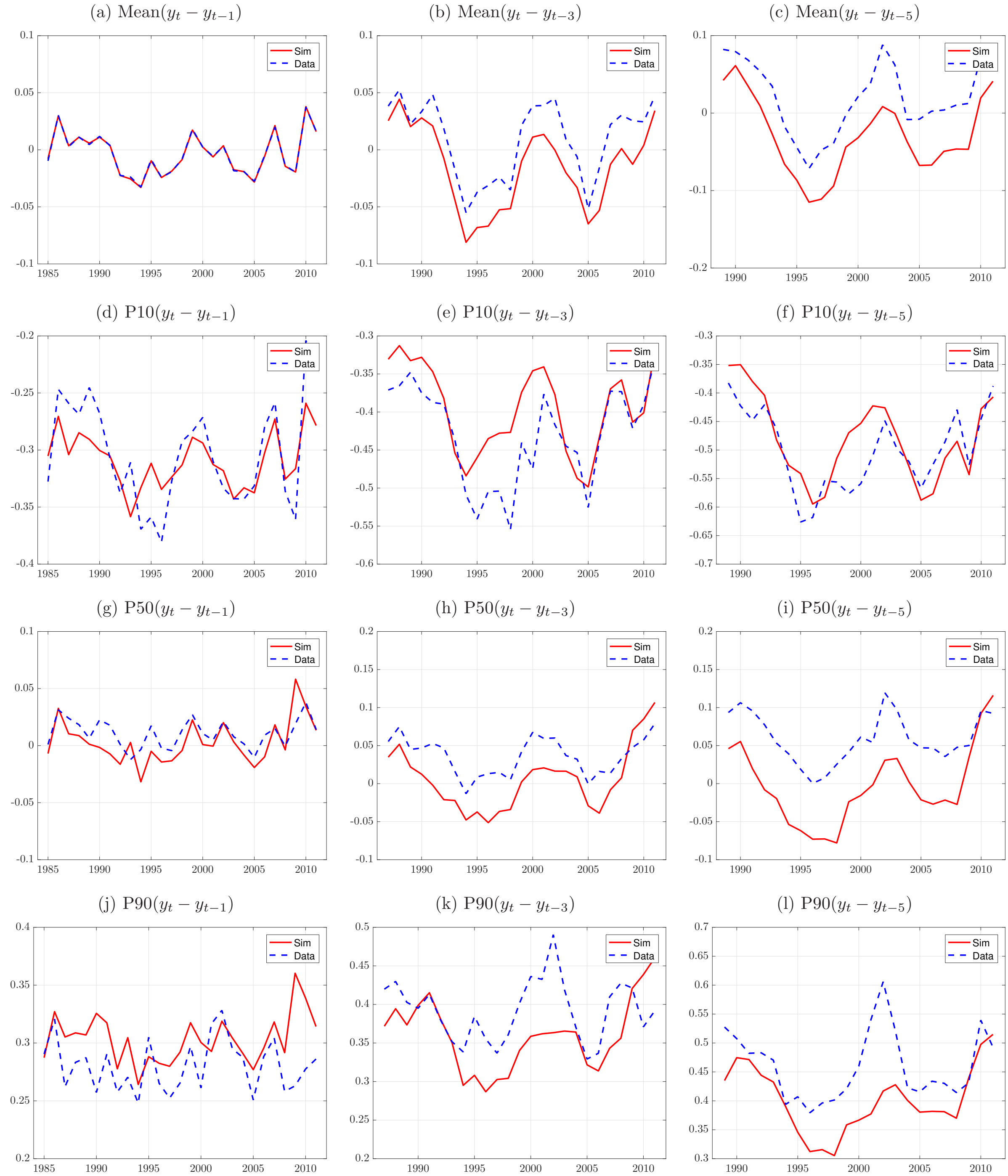
Note: Each panel shows the time series of a moment of short-run, medium-run, or long-run income changes together with the correspoinding moment implied by the estimated income process.

Figure B.5: Pre-Government Income Fit: Sweden



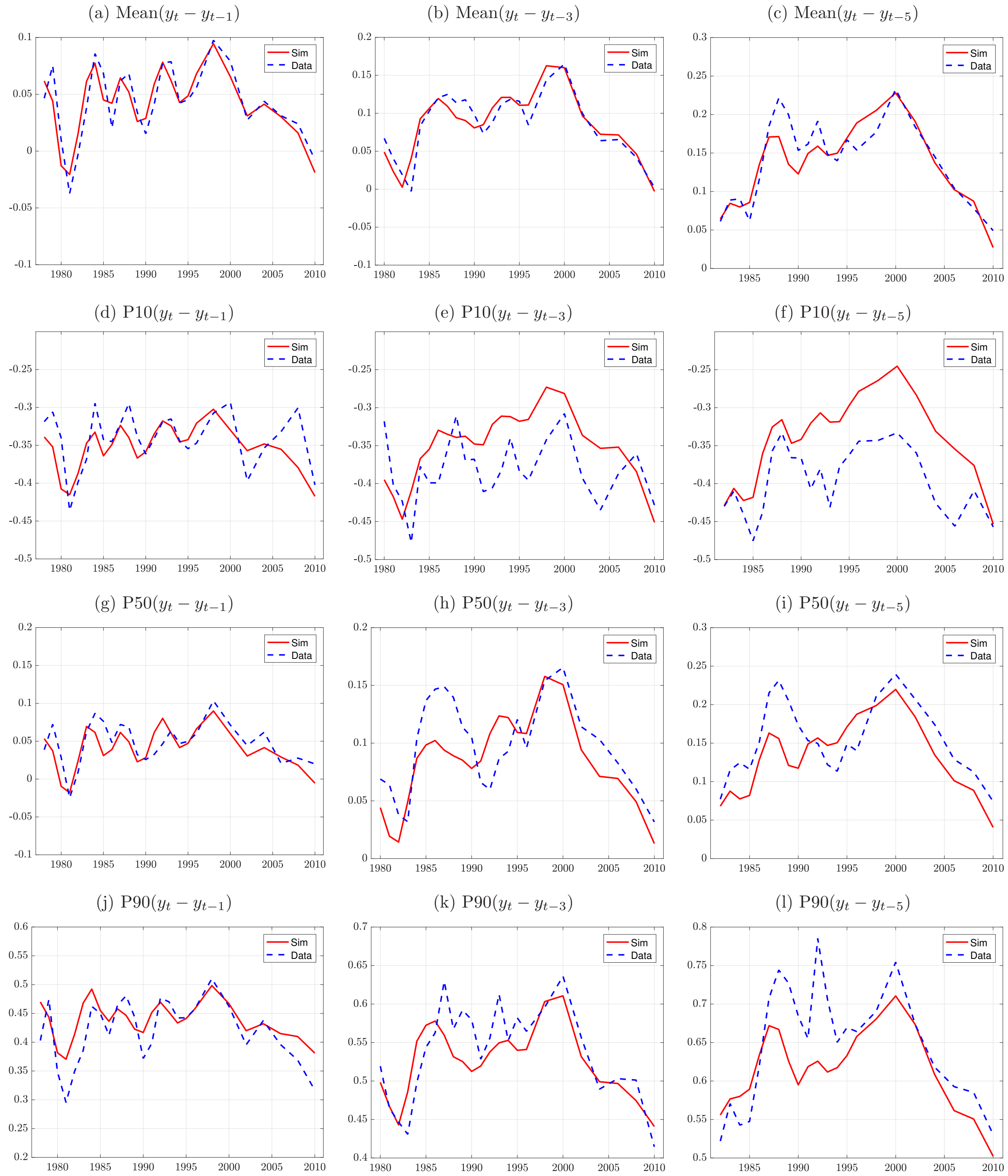
Note: See notes to figure B.4.

Figure B.6: Pre-Government Income Fit: Germany



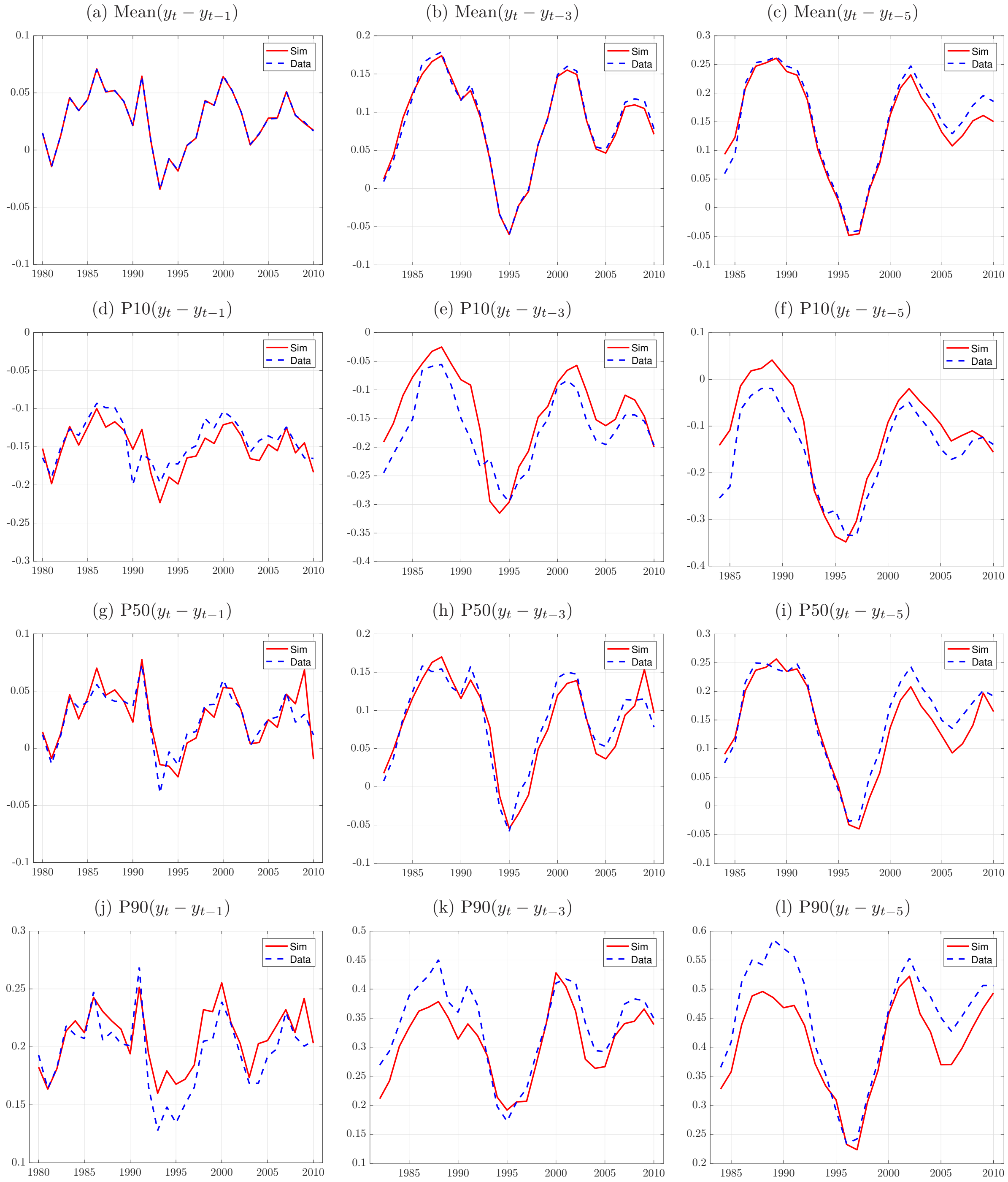
Note: See notes to figure B.4.

Figure B.7: Post-Government Income Fit: United States



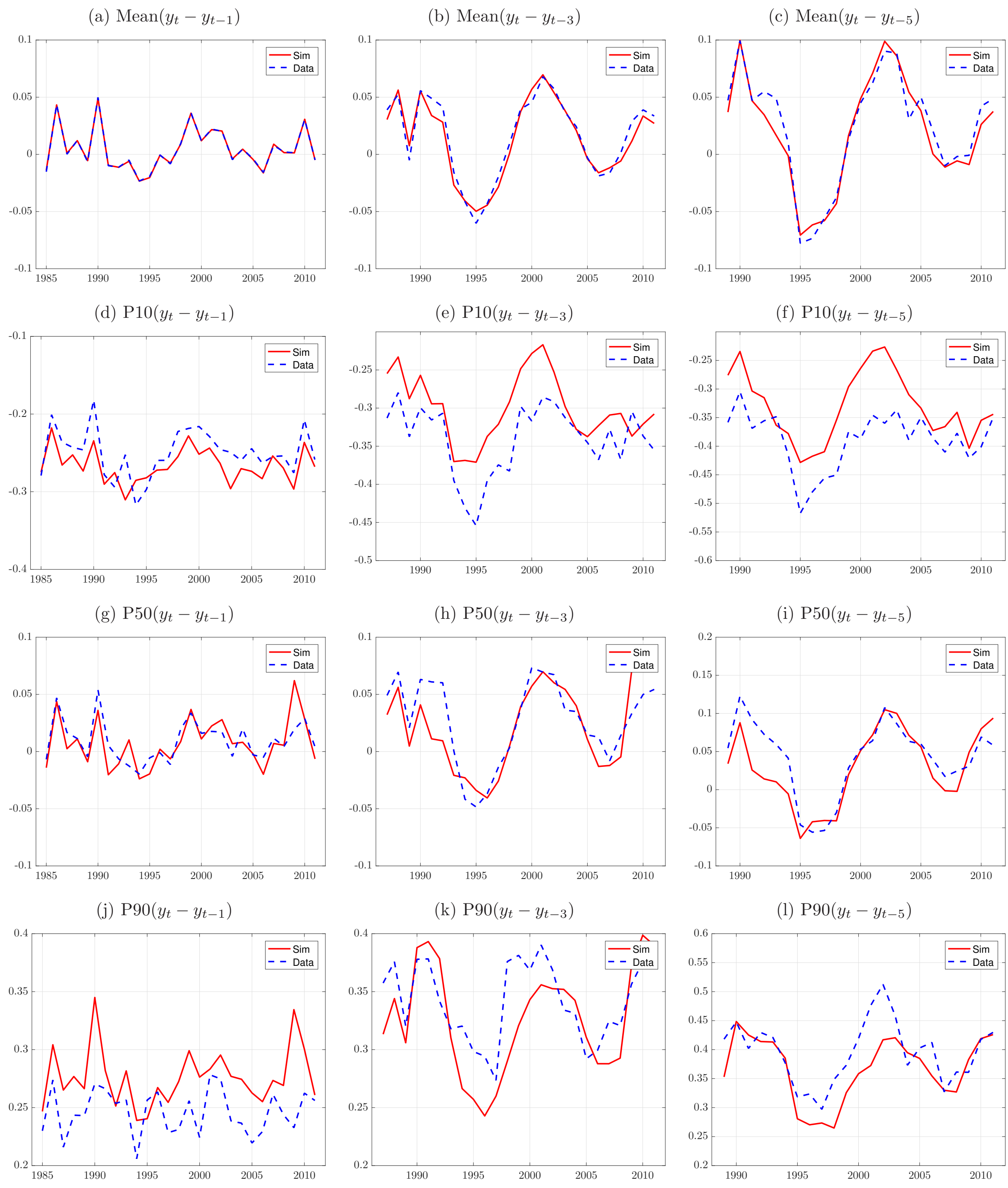
Note: See notes to figure B.4.

Figure B.8: Post-Government Income Fit: Sweden



Note: See notes to figure B.4.

Figure B.9: Post-Government Income Fit: Germany



Note: See notes to figure B.4.

B.6 Quantitative Model

Given estimates of the income process, we scale the parameters of the permanent shocks ζ to feed them into the model - fraction $\lambda$is insurable and the rest is uninsurable. This scaling implies that the first three standardized moments of the distribution of insurable shocks are given as below - for the first three moments of the uninsurable shocks, simply replace λ with $1-\lambda$.

$$
\begin{aligned}
E\left[\eta_t\right] &= \sum_{i=1}^{3} p_i \mu_{\eta,i,t} = \sum_{i=1}^{3} p_i \lambda^{1/2} \mu_{i,t} = \lambda^{1/2} \sum_{i=1}^{3} p_i \mu_{i,t} = \lambda^{1/2} E\left[\zeta_t\right] \equiv \lambda^{1/2} \mu_{\zeta,t} \\
var\left[\eta_t\right] &= \sum_{i=1}^{3} p_i \left(\sigma_{\eta,i}^2 + \mu_{\eta,i,t}^2\right) - \left(E\left[\eta_t\right]\right)^2 = \sum_{i=1}^{3} p_i \left(\lambda \sigma_i^2 + \lambda \mu_{i,t}^2\right) - \left(\lambda^{1/2} E\left[\zeta_t\right]\right)^2 \\
&= \lambda \left(\sum_{i=1}^{3} p_i \left(\sigma_i^2 + \mu_{i,t}^2\right) - E\left[\zeta_t\right]^2 \right) = \lambda var\left[\zeta_t\right] \\
skew\left[\eta_t\right] &= \frac{1}{var\left[\eta_t\right]^{3/2}} \sum_{i=1}^{3} p_i \left(\mu_{\eta,i,t} - E\left[\eta_t\right]\right) \left[3\sigma_{\eta,i}^2 + \left(\mu_{\eta,i,t} - E\left[\eta_t\right]\right)^2\right] \\
&= \frac{1}{\lambda^{3/2} var\left[\zeta_t\right]^{3/2}} \sum_{i=1}^{3} p_i \left(\lambda^{1/2}\mu_{i,t} - \lambda^{1/2} E\left[\zeta_t\right]\right) \left[3\lambda\sigma_i^2 + \left(\lambda^{1/2}\mu_{i,t} - \lambda^{1/2} E\left[\zeta_t\right]\right)^2\right] \\
&= \frac{1}{\lambda^{3/2} var\left[\zeta_t\right]^{3/2}} \sum_{i=1}^{3} p_i \lambda^{1/2} \left(\mu_{i,t} - E\left[\zeta_t\right]\right) \left[\lambda \left(3\sigma_i^2 + \left(\mu_{i,t} - E\left[\zeta_t\right]\right)^2\right)\right] \\
&= \frac{1}{var\left[\zeta_t\right]^{3/2}} \sum_{i=1}^{3} p_i \left(\mu_{i,t} - E\left[\zeta_t\right]\right) \left[\left(3\sigma_i^2 + \left(\mu_{i,t} - E\left[\zeta_t\right]\right)^2\right)\right] \\
&= skew\left[\zeta_t\right]
\end{aligned}
$$

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