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INCOME INEQUALITY IN OLD AGE

THREE ESSAYS ON THE FORMATION OF INEQUALITY DURING THE WORKING LIFE

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Abstract

This thesis examines the income inequality after retirement between the sexes and analyzes its formation process during the course of life. It shows the long-term consequences of decisions made during a working life and discusses the processes that cause the cost of these decisions - like the choice of a mini-job or an extended career interruption - to accumulate during the life course. For this reason, the cumulated life-time employment income as well as pensions are analyzed - due to the structure of the German pension system, both measures are very similar. The focus of earlier studies has often been laid on the short term consequences of such decisions in the course of life. Often, only the gender wage gap - the gender differences in earned income between men and women - is discussed in this context but, in times of demographic change and aging societies, pension differences are of substantially increased importance. The fundamental measure used in this thesis is the gender pension gap - similar to the concept of the gender pay gap, it measures the gender disparities in old-age income as relative difference between the average own pension incomes of men and women. This thesis is an empirical one and focuses on the situation in Germany. Consequently, German micro-data sets, mainly the German Socio-Economic Panel (SOEP) as well as the survey *Alterssicherung in Deutschland*, are used. The methods applied in this thesis are, to the most part, decomposition analysis as well as micro-simulation - a simulation model that is able to project employment biographies until retirement and to quantify the effects of policy changes in scenarios is developed and used. Hence, this thesis provides additional insight in the formation process of inequality, in the capability of politics to counteract this formation of inequality, and in the future development of gender differences in pensions. In the following, the contribution of each individual chapter is briefly discussed:

Chapter 2 discusses the gap in own old-age incomes of men and women and explores the causes for these differences by means of decomposition methods using German micro-data of the survey *Alterssicherung in Deutschland* (ASID). Since 1992 the gender pension gap has decreased but still amounts to about 60 % as of 2007. It is shown that this gap is mainly explained by differences in labor market experience and education. The gap is especially high at the lower end of the pension income distribution. The contribution of differing labor market experiences to the explained gap is particularly pronounced for retirees with low pensions.

The third chapter provides a micro-simulation study on the long-run effects of career interruptions in Germany, extending earlier work which generally only focuses on the first few years after an interruption. Using data of the German Socio-Economic Panel, it finds that career interruptions will, for the average individual, have lifelong effects on incomes and labor-force participation. It quantifies

these effects for the average affected individual as well as on the entire society. It therefore provides additional information on the total cost of career interruptions.

Chapter 4 discusses the expected future development of the gender pension gap in Germany and the influence of marginal employment on this development. To achieve this goal, a complex micro-simulation model is developed. It is able to project the gap for future as well as current retirees based on various micro-data sources. This chapter finds that the gender pension gap can be expected to continuously decrease over time. As of 2016, the gap in the statutory pension scheme is calculated to amount to about 52 percent. By 2038, the gap is predicted to decrease to 37 percent. In scenarios the effect of marginal employment on the gap is quantified - the consistent substitution of mini-jobs with regular part-time work decreases the gap by about 1.5 percentage points in the long run.

Zusammenfassung

Diese Arbeit befasst sich mit der Einkommensungleichheit zwischen den Geschlechtern im Alter und deren Entstehung im Lebensverlauf. Sie zeigt auf, welche Konsequenzen Entscheidungen während des Erwerbslebens in der langen Frist haben und durch welche Prozesse sich jene Entscheidungen, z.B. die Wahl eines Minijobs oder die Verlängerung einer Erwerbsunterbrechung, im Lebensverlauf kumulieren. Betrachtet werden dabei sowohl kumulierte Lebenseinkommen als auch Renten - durch die Gestaltung des deutschen Rentensystems sind beide Größen eng miteinander verwandt. Vorrangig untersucht wurden bisher die Unterschiede im Erwerbseinkommen zwischen Männern und Frauen - der sogenannte Gender Wage bzw. Pay Gap - jedoch gewinnen Rentenunterschiede in Zeiten des demographischen Wandels und der Alterung der Gesellschaft zunehmend an Bedeutung. Das grundlegende Maß für die Untersuchung ist, angelehnt an den Gender Pay Gap, der Gender Pension Gap. Dieser ist definiert als der relative Unterschied in den durchschnittlichen eigenen Alterseinkommen von Männern und Frauen. Die Arbeit ist empirisch geprägt und hat ihren Fokus auf der Analyse der Situation in Deutschland. Entsprechend beruhen alle Auswertungen auf deutschen Daten - hauptsächlich auf dem Sozio-oekonomischen Panel (SOEP) sowie der Umfrage Alterssicherung in Deutschland (ASID). Methodisch verwenden die Arbeiten sowohl Dekompositionsanalysen als auch ein eigens neu entwickeltes Mikrosimulationsmodell, das in der Lage ist Erwerbsbiographien bis zum Renteneintritt fortzuschreiben und das es ermöglicht innerhalb von Szenarien die Auswirkungen von Entscheidungen im Erwerbsleben zu quantifizieren. Damit liefert diese Arbeit neue Erkenntnisse zu den Entstehungsprozessen von Ungleichheit, zu den Möglichkeiten der Politik dieser Ungleichheit weiter entgegenzuwirken und auch zur Vorhersage des Gender Pension Gap in der Zukunft. Innerhalb der Beschreibung der einzelnen Kapitel werden die Ergebnisse kurz näher erläutert:

Kapitel 2 betrachtet den Unterschied in den Renteneinkommen aus eigenen Ansprüchen zwischen Männern und Frauen und untersucht die Ursachen der beobachteten Rentenlücke in Deutschland mittels Dekompositionsanalysen basierend auf den Daten der Befragung Alterssicherung in Deutschland. Es wird ferner beschrieben wie der Gender Pension Gap langsam gesunken ist, aber, auf Stand der Daten von 2007, noch immer 60 Prozent beträgt. Es wird gezeigt, dass diese Lücke vornehmlich durch Unterschiede in Erwerbserfahrung und Bildung erklärt werden kann. Es wird darüber hinaus ersichtlich, dass der Gap entlang der Einkommensverteilung deutlich variiert. Besonders hoch ist er für Gruppen mit niedrigen Einkommen und wird an dieser Stelle in viel stärkerem Maße durch Unterschiede in der Berufserfahrung erklärt als bei hohen Einkommen.

In Kapitel 3 wird ein komplexes Mikrosimulationsmodell zur Fortschreibung von Erwerbsbiogra-

phien entwickelt, das der Analyse der langfristigen Auswirkungen von Erwerbsunterbrechungen in Deutschland dient. Basierend auf den Daten des Sozio-oekonomischen Panels werden regressionsbasiert die Erwerbsbiographien der Befragten iterativ bis zur Rente fortgeschrieben. In Szenarien werden die langfristigen Kosten einer einjährigen Erwerbsunterbrechung berechnet. Es zeigt sich dabei, dass die Kosten einer Erwerbsunterbrechung für den durchschnittlichen Betroffenen im Lebensverlauf nur sehr langsam abnehmen und fast bis zum Renteneintritt deutlich bemerkbar sind. Dieses unterstreicht deutlich wie bedeutsam und langanhaltend die Folgen von Erwerbsunterbrechungen tatsächlich sind.

In Kapitel 4 wird das Modell aus Kapitel 3 substantiell erweitert. Es ist nun in der Lage den Gender Pension Gap in Deutschland für einen Zeitraum von 20 Jahren zu prognostizieren. Es wird erwartet, dass der Gender Pension Gap - der relative Abstand zwischen den eigenen Renteneinkommen von Männern und Frauen - in diesem Zeitraum auf ca. 38 Prozent zurückgehen wird. In Szenarien wird der Effekt des Minijobs auf die Rentenlücke untersucht - es zeigt sich dabei, dass Minijobs nicht nur auf individueller Ebene nachteilig sind, sondern, da besonders Frauen diese Erwerbsform wählen, auch den Gender Pension Gap offen halten. Würden Minijobs durch reguläre Teilzeitarbeitsverhältnisse ersetzt, so könnte der Gap - sehr langsam - bis 2038 um ca. 1,5 Prozent zusätzlich gesenkt werden.

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Chapter 1

Introduction

1.1 Motivation

Inequality is a phenomenon that has many facets and is frequently a topic of debate in the academic sector as well as in the general public and in politics. A particularly important part in this discussion is that on economic differences between the genders. In Germany, gender differences in many economic areas - from the number of women in managerial position up to the choice of a field of study - are of importance. But especially employment income differences between men and women are regularly a matter of debate.

In recent years, however, an increasing number of discussions has revolved around the observed income inequality between men and women in old age (see, for example, Flory (2011)). Demographic changes in aging societies like Germany make these problems especially clear. Low fertility rates over many years and increased life expectancy have lead - and will continue to lead - to a growing share of pensioners in Germany's population (see Statistisches Bundesamt (2016b)). Therefore, it is of central importance to examine what causes old-age inequality, how this inequality can be expected to develop in the future, and what politics can do to counteract the factors that are increasing inequality. This thesis attempts to answer these questions.

In Germany, the amount of pension is mainly determined by pension contributions in proportion to a person's earned income during employment.[1] Therefore, employment biography and lifetime income crucially determine inequality in old age, emphasizing the importance of the lifetime perspective. This is especially the case as decision made in one's employment life continue to have an effect for many years to come.

[1] Detailed information on the German pension system can be found in Boersch-Supan and Wilke (2004).

The remainder of this section is intended to provide an overall and non-quantitative introduction to old-age inequality as well as its formation in the course of life. It briefly discusses how the German pension systems leads to an accumulation of inequality, why the lifetime perspective is necessary, and the methods that can be used to model the formation of lifetime inequality. It further explains why 'mini-jobs' and career interruptions, two central topics of the forthcoming chapters, are important factors in generating old-age inequality. Section 1.2 describes the contributions of this thesis: first with respect to the overall topic and then focused on the individual chapters. Section 1.3 briefly summarizes the three chapters. Finally, Section 1.4 describes the two specific aspects that are relevant for all chapters: It shows how the employment rates of men and women have converged and how the demographic development leads to an aging society. This emphasizes the importance of the topic old-age gender inequality and its formation process.

Inequality in old age and its causes are the central topics of discussion in this thesis. Specifically, the gap in own pension incomes between the sexes is considered. The measure that is used to quantify this inequality is the gender pension gap - the relative difference between the average own pension incomes of men and women. In Germany, pension incomes from its first and by far most important pillar - the statutory pension scheme - mirror a person's employment biography. During a work life, up to two earning points can be received each year, whereby the number of points is determined by the relationship between individual and average income. A person receiving only one half of Germany's average wage will consequently get half an earning point in that specific year. The accumulated earning points are the main determinant of the pension income - a more thorough discussion of the German pension system is, for example provided by Rürup (2002) or Chapter 2.

In principle, other ways to measure inequality than the one used to describe the gender disparities in pensions are conceivable. A complete discussion can, however, not be provided at this point - a general discussion of the fundamental concepts of inequality metrics can, for example, be found in Allison (1978) and Atkinson (1970). Many of these measures were originally intended to quantify the amount of inequality within an (income) distribution. The 'Gini Index' (see Gini (1921)) is most likely the best-known example for such an inequality metric. There are, nevertheless, methods available that allow decomposing the inequality measure within and between group parts (see, for example, Bourguignon (1979) or Shorrocks (1980)). Also, more straightforward approaches are possible - like, for example, a comparison between coefficients of variation (see Champernowne and Cowell (1998)). The gender pension gap is, however, not only an intuitive and straightforward measure of inequality, it also, most importantly, directly relates to the measure of wage inequality: the gender wage gap.

The gender wage gap has the same structure as the gender pension gap - it is measured as the relative difference between the average hourly wage rates of men and women (see Weichselbaumer and Winter-Ebmer (2005)) and often serves as the basis for the examination of inequality during the employment life (see, for example, Kunze et al. (2017) for a recent review of the topic). Frequently, discussions evolve around the question whether or to what degree gender wage differences are a result of discrimination. In fact, Oaxaca (1973) designed his decomposition method with the intention of answering this very question. Gender wage and pension gap are closely related, as gender wage differences accumulate over an individual's working life and therefore contribute to a substantial part of the pension disparities (see Boll et al. (2017) and Grabka et al. (2017)). Moreover, with the intention of providing a quantification of lifetime income differences, the gender overall earnings gap was introduced by Eurostat (see also Bettio (2017)) incorporating hourly earnings, hours paid, as well as well employment rates in the measure.

Nevertheless, the concept of the gender pension gap is not without criticism. Faik and Köhler-Rama (2012) argue that the gender pension gap is an improper measure as it is neither well-suited to depict a society's old-age poverty nor able to measure welfare disparities. While it is correct that the gender pension gap does not capture poverty or welfare, it has to be stated that this measure was never intended to do so. The gender pension gap focuses on the personal pension income and should therefore rather be seen in the context of economic independence and not uniquely on welfare (see also Bettio et al. (2013) for a discussion of the purpose of the gender pension gap). Furthermore, the gender pension gap is, due to the nature of the German pension system, also a measure of lifetime employment inequality. Certainly, the gender pension gap does not make any statement on the fairness of the German pension system (which is clearly not discriminatory towards women). The gender pension gap is a descriptive measure of gender differences in personal pension incomes. Reasons for these differences are discussed in the following chapters.

It is certainly true that these gender differences in pensions will continue to gain in importance in the coming years as Germany and many other European countries are confronted by dramatic demographic changes and aging societies (see Statistisches Bundesamt (2015)).[2] These demographic challenges arose due to persistently low fertility rates (see Pötzsch (2017)) - that only have started to increase in very recent times - and a constant rise in life expectancy (see Statistisches Bundesamt

[2]Due to the importance of this topic as background information for this thesis, Section 1.4 is devoted entirely to this discussion.

(2017)). The retirement of the baby boomer generation will further increase the importance of this topic and put additional stress on the German pension system (see, for example, Börsch-Supan et al. (2016)).

Above, it was discussed that due to the functionality of the German pension system gender, inequality in pensions originates from wage disparities and employment decisions in the course of a working life. It is therefore of utmost importance to determine how exactly these differences emerge, how they can be influenced, and how they are expected to develop in the future. When answering these questions, two positions can be - and are - taken: a retrospective one, looking at current retirees answering the question on how their gender income difference emerged, and a forward-looking perspective, modeling biographies and thereby the building up process and the future development of gender inequality. The forward-looking perspective has the distinct advantage that it is straightforward to incorporate ongoing developments that are influencing the gender pension gap as, for example, the differences in the employment patterns of men and women are continuously diminishing as result of increasing labor force participation rates of women (see Statistisches Bundesamt (2016b) or Section 1.4). This trend is a result of social changes but also a consequence of reforms and new policies. For example, a new form of parental allowance (the so-called *Elterngeld*) has led to increased participation rates of women in the second year after childbirth (see Huebener et al. (2016)), were able to influence social norms as Unterhofer et al. (2017) suggest, and also improved child-care opportunities (see Bauernschuster and Schlotter (2015)).

From a methodological standpoint, different approaches are available to cover both the retrospective as well as the forward-looking angle. In particular, decomposition methods allow us to look back at biographies in order to analyze the causes of income disparities of current retirees. The classic starting point for such a study is the Oaxaca-Blinder-method (see Oaxaca (1973) and Blinder (1973)), that allows decomposing the gap in a part related to endowment differences and a part that is caused by differing returns to these endowments. Both parts can be further subdivided into shares related to a specific endowment (like age, employment years, or education). It is certainly possible that the gender pension gap will differ for varying income groups; from a political perspective, a gap that is solely driven by high-income pensioners is surely assessed differently than one that is mainly caused by retirees with low income. However, the approach by Oaxaca and Blinder does not work when applied to non-linear functions, insomuch that other methods have to be used (see, for example, Bauer and Sinning (2008) for a possible extension of the Oaxaca-Blinder-method). For the analysis of distribution quantiles, this thesis follows an approach using RIF regression developed by Firpo et al. (2007)

that allows decompositions in the spirit of Oaxaca and Blinder.

Micro-simulation, on the other hand, is a viable option to model the forward-looking perspective. The field of micro-simulation models is wide and offers numerous solutions to different problems (for an overview, see Merz (1991)). Static models are, for example, used to quantify the cost of policy changes (see Flory and Stöwhase (2012) for an illustration) while dynamic approaches are able to capture the adjustment process of human behavior. In this thesis, a new micro-simulation model which projects employment biographies based on empirically estimated transition probabilities is developed and used. The model is able to capture the long-ranging consequences of events during one's employment life, as, for example, career interruptions can have a long aftermath (see Mincer and Ofek (1982) and Beblo and Wolf (2002)). Such events are able to influence the entire remaining biography. Certainly, there are other possible approaches to model or project employment biographies. Geyer and Steiner (2014), for example, directly estimate and predict the number of years to be spend in certain states (like full- and part-time employment) without explicitly determining the sequence in which these states occur. Westermeier et al. (2012), on the other hand, complete employment biographies through assigning the subsequent biography of older individuals to that of younger ones by means of statistical matching. Other approaches, like, for example, explicitly modeling preferences in structural models may also be a way forward (see, for example, Michalopoulos et al. (1992) or Haan and Wrohlich (2011) for models in the context of employment and child care). The main advantages of the chosen approach are its flexibility, the fact that it is purely driven by empirical evidence, as well as, contrary to other models, the ability to incorporate recent developments. Furthermore, the chosen approach allows for the implementation of counter-factual scenarios and is thereby able to quantify the long-term consequences of decisions made during an individual's employment life.

Essentially, there are some datasets available that can be used to build the specified micro-simulation model - however, none of them is optimal with respect to any desired aspect. As core data for this simulation model, the Socio-Economic Panel (SOEP) was chosen (see Wagner et al. (2007)) as it provides detailed socio-economic characteristics, a panel structure, as well as a reasonably large number of respondents.[3] The SOEP, nonetheless, does not provide information on the different sources of pension income with the same level of detail as the *Alterssicherung in Deutschland* survey (see Kortmann and Heckmann (2012)) which was therefore chosen as the basis of the decomposition analysis and is also used in addition to the SOEP data in the micro-simulation model to provide information on current retirees. Naturally, the SOEP is not able to provide information

[3]Compared to other datasets like the German micro-census, the SOEP, with its more than 20,000 respondents, is still relatively small. But, on the other hand, it benefits heavily from its wealth of information and its panel structure.

on income or earning points in periods before an individual joins the panel[4] and therefore additional information is needed. This can either be accomplished by imputing the necessary variables (for more information see, for example, Allison (2002)) or by matching (see Rässler (2002)) the SOEP with another dataset. Here, the *Versicherungskontenstichprobe* was chosen as it provides official data on earned pension claims. The main alternative to the SOEP when building a micro-simulation model for this specific purpose is the data of the *Stichprobe der Integrierten Arbeitsmarktbiografien* (SIAB), a large panel data with detailed and official information on employment biographies.[5] The main disadvantage of the SIAB and the reason for choosing the SOEP for building up the simulation model is, however, its scarce information on socio-economic characteristics. This makes the estimation of transition equation as well as matching procedures much harder due to the limited information.

The gender pension gap is, as described above, influenced by the entire employment biography. This is particularly the case when these biographies, entirely or in parts, differ between the average man and woman. It has, for example, to be noted that, despite of all changes, career interruptions are still a particularly female phenomenon (see Chapter 3). This holds, especially true for the care of elderly relatives (see Michaud et al. (2010) or Ciani (2012)) as well as children (see, for example, Kreyenfeld and Hank (2000)). It is well known that career interruption will have a long-lasting effect on the individual biography (see also Kreyenfeld and Hank (2000)), little is, however, known how long-lasting they will exactly be on average. Given that employment experience is closely related to the likelihood of being employed (see Mincer (1974)), entire biographies will be affected by interruptions emphasizing the importance of a lifetime perspective in this discussion. Additionally, substantially more women than men choose a German form of marginal employment: the mini-job (see Weinkopf (2009) or Scheele (2013)). Due to the design of the mini-job, the incentives to switch to regular employment are low and most mini-jobbers earn wages right up to the mini-job boundary (see also Tazhitdinova (2017) for further details); thus, the mini-job is likely to be a factor in keeping the gender pension gap open. Albeit, no quantitative information on this topic is available. Hence, naturally the question emerges on how exactly the gender pension gap would change if these persons working in mini-jobs were given the opportunity to have regular, part-time employment.

In summary, it can therefore be stated that the goal of this thesis is to provide new quantitative information on the determinants of old-age income inequality and its formation in younger years. Furthermore, it develops and describes new tools to achieve this goal. The focus of all three chapters lies on the income inequality of German retirees and its causes during the life course. They pay special

[4]Retrospective information on a person's employment biography is, however, available.
[5]More information can be found in D'Orazio et al. (2006).

attention to two specific aspects: The starting point in Chapter 2 is the discussion of the gender pension gap - the observation that women only receive 40 percent of the old-age income of men.[6] Decomposition analysis shows that the gap mainly arises due to disparities in employment experience and education, where the employment differences are particularly important for low-income pensioners while, at the other end of the pension income distribution, differences in education have a much more pronounced effect. It is also first time that that decomposition methods for distribution quantiles are used in the context of old-age incomes. The third and fourth chapter discuss specific aspects of the employment life and how decisions in this phase can have long-term effects resulting in the observed old-age inequality.[7] In particular, Chapter 3 discusses the lifetime effects of career interruptions and shows how these will change the average entire employment path in a way that substantially exceeds the short-term effects of the interruption. This leads to gender differences at an old age. It is, however, not the case that any form of employment will be beneficial to security at an old age as the gains from mini-jobs are small.[8] Therefore, Chapter 4 discusses the role of the mini-job and its influence on old-age income and the gender pension gap. Additionally, Chapter 3 describes the development of a new micro-simulation model[9] that allows the necessary forecast of employment biographies until retirement, the specification of scenarios, and the aggregation of results. In Chapter 4, this model is extended to capture a wider scope of dynamics, also including the retired population to predict the gender pension gap.

The results are also relevant from the political perspective, given that they shed light in the causes of the development of inequality at an old age and thereby provide insight in the use of political measures that can counteract undesirable developments. The essays focus on the situation in Germany and have to be read in the context of the current challenges (e.g., with respect to the demographic development) with respect to pension system. However, many conditions are similar in other European countries: The gender pension gaps in Austria, Great Britain or the Netherlands are not significantly smaller than the German one. Italy and Spain are facing similar problems with respect to low fertility rates and an aging society. Consequently, the following discussion is also of interest in a wider European context.

[6] See also Rasner (2014).
[7] Different approaches in modeling the employment life can, for example, be found in Haan et al. (2017) or Geyer and Steiner (2014).
[8] See also Galassi (2017).
[9] For detailed information about micro-simulation, see, for example, Merz (1994).

1.2 Contribution

This thesis contributes to several topics: First and foremost, it is part of the discussion on gender inequality.[10] Additionally, it has a special focus on pensions. While in the course of these discussions the gender pay gap is most frequently examined (see Plantenga and Remery (2006)), gender differences in pensions are of utmost importance. This is particularly the case as the ongoing demographic change causes to German society to age substantially. On the other hand, adjustment processes with respect to employment rates and wage between the genders can be observed. Therefore, this thesis does not only provide retrospective information on the gender pension gap but is - for the first time - able to make long-term predictions about its development. For this reason, the formation process of gender inequality until retirement is explicitly modeled in Chapters 3 and 4.

The model used in this thesis explicitly takes the lifetime perspective in the formation of inequality into account. This is particularly important as the gender pension gap provides more information than merely that on pension differences because, due the nature of the German pension system, it also summarizes the disparities in the entire employment biographies of men and women. This lifetime perspective is therefore often extremely useful for discussion of pension issues (see also Söhn and Mika (2017) or Mika (2017)). Thus, the development of gender wage gap and the adjustment process of employment rates is inherently also described within this framework since these differences accumulate in the course of life and will ultimately result in the gender pension gap.

To tackle these topics, new models and methods are developed and used. This thesis thereby provides additional insight and new approaches in the modeling of employment biographies (see also Westermeier et al. (2012) or Geyer and Steiner (2014)) by means of behavioral micro-simulation. The approach of this micro-simulation model is purely driven by empirical analysis and intended to rely as little as possible on assumptions while, at the same time, being able to incorporate the most recent social developments. In particular, the model is designed to project employment biography iteratively by estimating transition probabilities between employment states and updating individual information (see Chapter 3 for details). Thereby, this thesis is able to provide a new approach for the projection of employment biographies and contributes by adding model variety. The new approach is not only able to deliver results for the average individual but also calculates aggregate results for the entire society. Additionally, this thesis uses non-linear decomposition techniques for the first time in the context of pension incomes. It is therefore able to discuss the development of the gender pension gap from two perspectives: retrospectively by examining the completed biographies of current retirees and looking

[10] See also Westermeier et al. (2017).

forward by projecting the biographies of those of younger age.

A new feature of this model is its ability to quantify scenarios: the basic idea is to alter biographies by changing initial conditions or outcomes within the projection horizon and to compare the model outcomes with those of a baseline scenario without any alternation. This thesis thereby provides a new tool to determine the long-term consequences of decisions during an individual's working life. In particular, this approach is used to receive detailed knowledge on the consequences of mini-jobs and career interruptions - two factors that are expected to influence the gender pension gap. But the model does not only quantify the overall effect of that sort of decision; it is also able to determine when the effects of such changes will occur. Therefore, this approach is also valuable from a social point of view as it helps to determine the consequences of policy changes and individual decisions made during an individual's employment biography.

In particular, the individual chapters provide contributions in the following manner: The second chapter extends earlier work (see Frommert and Strauß (2013)) discussing the decomposition of the German gender pension gap to an inspection of all its components and does, for the first time, not only focus on the pension system's first pillar. It also, and most notably, goes beyond these previous approaches by examining whether the pension gap is constant over the old-age income distribution and, furthermore, examines whether the causes of the gap are also different for different pension incomes. The results suggest that the gap does in fact decline for higher incomes and that the main cause of the gender pension gap shifts from differences in employment experience to education disparities. For the first time, the decomposition methods for quantiles - as discussed in Firpo et al. (2007) and Firpo et al. (2009) - are used to examine gender differences in old-age income. The third chapter provides additional knowledge on the formation of inequality in the life course. It discusses how employment interruptions affect the remaining career path[11] - a topic that is particularly relevant with respect to the gender pension gap as comparatively more women than men interrupt their careers. In contrast to many other discussions, Chapter 3 not only considers biographies that are continued without further interruptions, it also examines the total consequences of an average employment break. The simulations suggest that the effects of an employment break do only diminish extremely slow and that this decline will only be heavily noticeable shorty before retirement. Going beyond earlier research, the newly developed behavioral micro-simulation model is also able to quantify the aggregate cost of a career interruption. Chapter 4 provides - for the first time - a long-term projection of the gender pension gap. The results suggest that the gap is expected to decrease below 40 percent by the late

[11] See also Beblo and Wolf (2002) for additional information.

2030s. Also for the first time, this approach is able to examine the effects of mini-jobs on the long-term development of the gender pension gap[12] - it is shown that choosing a regular part-time employment instead of mini-jobs from this day on would decrease the gender pension gap by about 1.5 percentage points in the late 2030s. It thereby provides additional evidence that mini-jobs are not only damaging on the individual but also on the society-wide level.

The following section provides a brief but more detailed summary of the individual chapters.

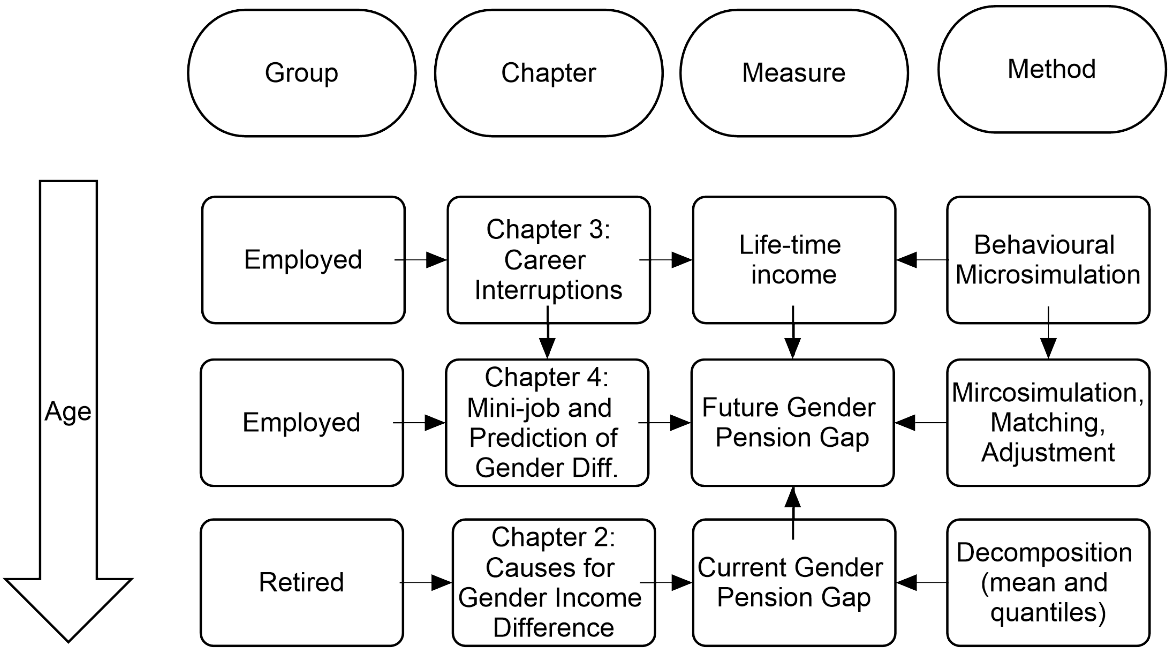
1.3 Summary

The starting point for all future considerations is the quantification of the gender pension gap in Chapter 2. By means of decomposition analysis, it is further shown that the gender differences in old-age income mainly arise due to different employment biographies of men and women. This static view is, however, not able to capture the building-up process of these differences in younger years. Therefore, a dynamic behavioral micro-simulation approach that can model the biographies of individuals of working age is chosen in Chapter 3. Here, how career interruptions affect employment biographies - with this effect being measured in terms of life-time income - is examined. There is an immediate connection to the results of Chapter 2 as in the German pension system, lifetime income and pension are heavily correlated. Given that an alignment process in the employment biographies of men and women can be observed, it can be expected that the gender gap in pensions will also decrease. The speed of this decrease is, however, unknown. For this reason, Chapter 4 substantially extends Chapter 3's model and predicts the long-term development of the gender pension gap and discusses the extent that a job has to have in order to be beneficial in closing the gap. This, in turn, leads back to the starting point of the discussion in Chapter 2, as the assumptions stipulated there not only are now shown to be true but can also be quantified. Figure 1.1 summarizes this discussion and the connection among the chapters in a schematic illustration.

CHAPTER 2. Chapter 2 discusses the gender differences in own old-age income and examines the causes for these differences for the average pensioner as well as for specific income groups, particularly for those with especially high or low pensions. These gender pension differences are measured by the gender pension gap. Following the lines of the gender pay gap (see, for example, O'Reilly et al. (2015)), the gender pension gap is defined as the relative deviation of the average women's pension income compared to that of men. The data shows that the gender pension gap amounts to about

[12]The relevance of the mini-job on the development of the gender pension gap arises due to the fact that substantially more women than men have chosen this form of employment (see, for example, Körner et al. (2013)).

Figure 1.1
Schematic illustration of content of and connection between the individual chapters



Source: Own illustration

60 percent, meaning that women's own pension claims only amount to 40 percent of those of men. This gap is, however, not constant in various aspects: First, an analysis over time suggests that the gender pension gap is constantly decreasing and, second, that the gap is different in size for different quantiles of the respective pension income distribution of men and women. The gap is particularly large for retirees with low personal pension income.

Contrary to previous studies (see, for example, Frommert and Strauß (2013)), Chapter 2 considers the pension incomes from all pillars of the German pension system (with the statutory pension plan being by far the dominant one - see, for example, Börsch-Supan et al. (2015)). This first pillar is so important that nearly all German retirees receive income from it. This pillar is therefore basically representative of the total pension income of the entire elderly population in Germany. This is not surprising, since most employments (as well as child-rearing periods) will lead to pension claims from this pillar. One data source is particularly useful for examining pension-related questions as it captures all aspects of the pension income, underlying income biography as well as socio-demographic information: the *Alterssicherung in Deutschland* (ASID) survey which is used in this analysis.

The focus of the study is to examine the causes of the gender pension gap. An extremely useful tool to achieve this goal is decomposition analysis. Oaxaca (1973) and Blinder (1973) are pioneers in the development and use of this technique, which aims at partitioning the average pension difference in shares related to endowments (such as the number of employment years and educational attainment) and in a part associated with the returns of this very endowments. These parts, the so-called explained and unexplained gap, can be further broken down to the individual contributions of the specific endowment. The extension of this method to other moments beside the mean is, however, not straightforward: this study follows a decomposition approach based on RIF regressions in the spirit of Firpo et al. (2007) and Firpo et al. (2009) - also suitable for distribution quantiles. It is the first to use their method in the context of the old-age income distributions.

This analysis shows that the largest part of the explained gender pension gap is due to gender differences in employment experience with the next important cause being disparities in education. It is, however, very interesting to see that the causes of the gap are not constant across the pension income distribution. In the quantiles below the median of this distribution where the gap is actually the largest, employment experience is the dominant force in driving the gap. Here, it is important to note that this is not simply caused by a substantial number of women having no own pension claims beside those resulting from child-rearing periods. In fact, the difference the sexes with respect to the fraction without any employment experience only amounts to about five percentage points. In the higher quantiles, on the other hand, the gap is mainly driven by education disparities. Consequently, increased labor force participation of women with previously only short employment spells is the most important determinant in closing the gender pension gap. How increases in employment rates precisely carry over to lifetime income and pension is discussed in detail in Chapters 3 and 4.

CHAPTER 3. It is well known that career interruptions are a major source in determining wages and pensions and consequently poverty and inequality at an older age (see Boll (2011b) or Ejrnaes and Kunze (2013)). However, much less is known about the exact size of the lifetime cost of an interruption. Chapter 3 answers this question for both the average individual as well as the entire society. It is most important to note that employment breaks not only have a short-term effect (i.e., the wage loss in the time without employment) but will also influence the entire future biography. Employment experience pays off in wages[13] and reduces the likelihood of ending an employment again. An increased number or longer interruptions raises the difficulty in finding a new job. These are some of the lifetime costs of interruptions that Chapter 3 addresses when studying the financial consequences of employment breaks.

In order to quantify these costs, a new micro-simulation model to predict employment biographies was developed, programmed, and used. The new empirical and regression-based model uses the panel

[13] See, for example, Mincer (1974).

data of the German Socio-Economic Panel (SOEP): In a first step, the transition probabilities between phases with and without employment are estimated based on socio-demographic characteristics - particularly the length and timing of career interruptions. In a similar way, the determinants of employment hours and wages are estimated. Using these estimates, predicted probabilities for changes in and out of employment can be calculated and, based on these probabilities and a corresponding chance outcome, the employment status of the next period is determined for each sample member individually. Employment hours and wages are then predicted based on the respective estimation equations. This process is iteratively repeated until retirement. After each iteration, the individual characteristics influencing the next period (such as employment experience or the time since the last interruptions) are updated. To account for the random element in the prediction, the entire process is repeated 100 times and average results are discussed.

Scenarios compare the aggregated projected lifetime income for the actual conditions of the individual with an interruption as given by the SOEP data with a hypothetical projected biography in which a past employment break is assumed to be one year shorter. The comparison of the projected costs in baseline and alternative scenarios reveals the overall cost of one year of employment interruption. Beside the comparison of the overall cost, the model is able to compare the aggregation processes between baseline and alternative scenarios. The results show that the follow-up cost of a career interruption is in fact substantial and not negligible, even at the society-wide level. The most important finding is, however, that the average subsequent cost of such an employment break are extremely long-lasting and are only starting to diminish shortly before retirement. In fact, these costs are nearly as high in the second half of the period between reentry and retirement as in the first.

The insight that career interruptions have such a long-lasting effect on the average affected person is of importance for both the individual decision process when considering a (predictable) interruption as well as for policies encouraging or discouraging employment. However, not all forms of employments are equally sensible with respect to security and independence at an old age - this is discussed in Chapter 4.

CHAPTER 4. Chapter 4 connects chapters 2 and 3 and is the link between the projection of employment biographies and the gender pension gap. By combining and extending both methodologies, it is possible to forecast the development of the gap for the next 20 years. By means of scenarios in the simulation model, the extent to which policy measure are able to close the gender pension gap can be approximated. Special focus is laid on the role of the mini-job (see Körner et al. (2013) for details on mini-jobs) in keeping the gender pension gap open, given that mini-jobs are predominantly chosen by women and might therefore be a major influence on old-age inequality.

To achieve these goals, the simulation model of Chapter 3 is expanded extensively. The state space of the projection is augmented and full-time work, part-time work, and mini-jobs are included in the simulation model. This richer state spaced demanded for an extension of the transition model which is now estimated by several multinomial logit models. To capture the specific nature of the mini-job - a substantial fraction of the mini-jobbers received a wage exactly at the mini-job threshold[14] - one-inflated beta regressions are used in the wage estimations for the mini-jobbers. In order to gain information on the gender pension gap in the already completed part of the employment biographies, official social security data (the *Versicherungskontenstichprobe*) is used. This micro-data set is matched with the data of the Socio-Economic Panel (SOEP) to predict the gap of the future retirees. The gap of the current retirees is examined with the help of micro-data on pensions as provided by the survey *Alterssicherung in Deutschland*. This allows for the projection of the gender pension gap for current pensioners. By combining both results, the development of the overall gap can be projected.

The current gender pension gap in the statutory pension scheme is estimated to amount to approximately 52 percent. The model projects an ongoing decrease in this gap though the speed of the decrease is expected to slow down slightly. A final gap of about 37 percent in 2038 is projected. This decrease is due to an adjustment process between the employment biographies of men and women. Scenarios provide the possibilities to sound out the magnitude of change in the gender pension gap that can be reached by political measures. Here, specific focus is laid on the role of the mini-job. It is shown that a substitution of mini-jobs with regular part-time employment for all current and future mini-jobbers will close the gender pension gap by approximately 1.5 percent. This finding is indicative of two results: firstly, the mini-job plays a non-negligible role in keeping the gender pension gap open but, secondly, any political attempt to close the gender pension gap in the short run by means of changes in the mini-job would be in vain, as the simulation is able to quantify how slow the transition process of policies really is.

1.4 Background and relevance

The following chapters extensively discuss developments in employment, the importance of the lifetime perspective, and the relevance of old-age issues. Those chapters have, however, the goal to predict future developments and do not particularly aim at looking back. Therefore, it is the intention

[14] See Tazhitdinova (2017) and Steiner and Wrohlich (2005b).

of this section to add an additional retrospective point of view to these predictions in order to put them in context. For this reason, the following pages will briefly describe the past developments of the factors that are be relevant throughout the next chapters and thereby also provides insight on why the life-time perspective and the gender pension gap are important issues in the current discussion. Firstly, trends in employment are examined - specific focus is laid on gender differences in employment and their past alignment processes that also form the basis for the later predictions. Afterward, the demographic development that causes the increasing importance of pension topics will briefly be discussed.

1.4.1 Gender differences in employment

Figure 1.2[15], shows the employment rates for five-year age-groups with the youngest age in each group depicted on the horizontal axis. This figure compares the age-specific employment rates between men and women and also in time.

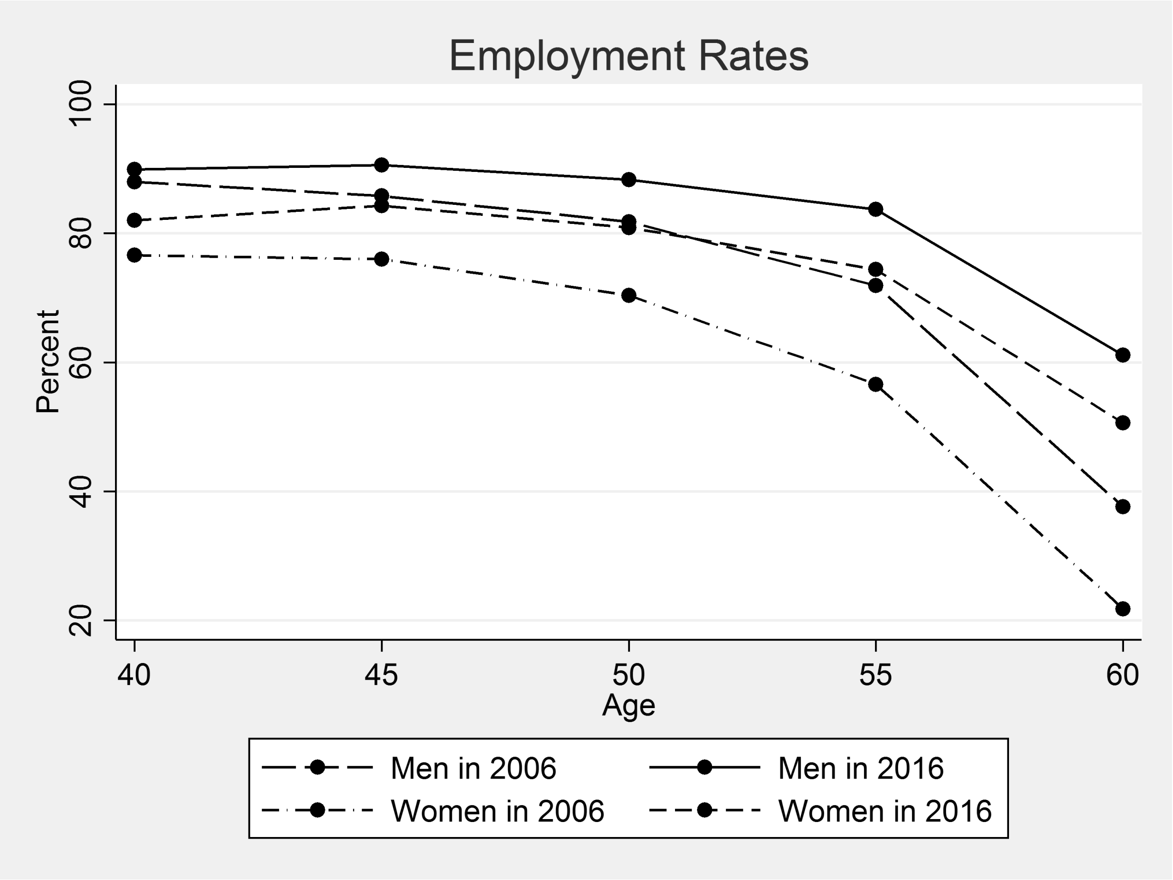
It can clearly be seen that there have been substantial changes in employment behavior within the comparatively short interval of only ten years. It is not surprising that, for both men and women, the employment rate declines while age progresses. It is, however, most interesting to see how dramatically the gender differences have decreased - a fact that is observable for all age-groups. This happened despite of the fact that men's employment rates have also risen between 2006 and 2016. The employment rates of women have now approximately reached those of men in the year 2006. This fast alignment processes have certainly to be considered in the modeling of employment lives and gender differences as it is done in the following chapters.

In Figure 1.3[16], the long-term development of employment rates of men and women since the early 1990s can be seen. Here too, the adjustment processes between men and women are clearly visible. While the employment rates of men have even declined for some periods of time, those of women have continuously risen since 1991. While the employment rate difference amounted to more than 20 percentage points back in 1991, this figure has diminished to significantly less than 10 percentage points in current times. Clearly, this process should also be contributing to a decline in the gender pension gap.

[15] see Statistisches Bundesamt: `https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/Arbeitsmarkt/Erwerbstaetigkeit/TabellenArbeitskraefteerhebung/ET_ETQ.html` (accessed July 13, 2018)

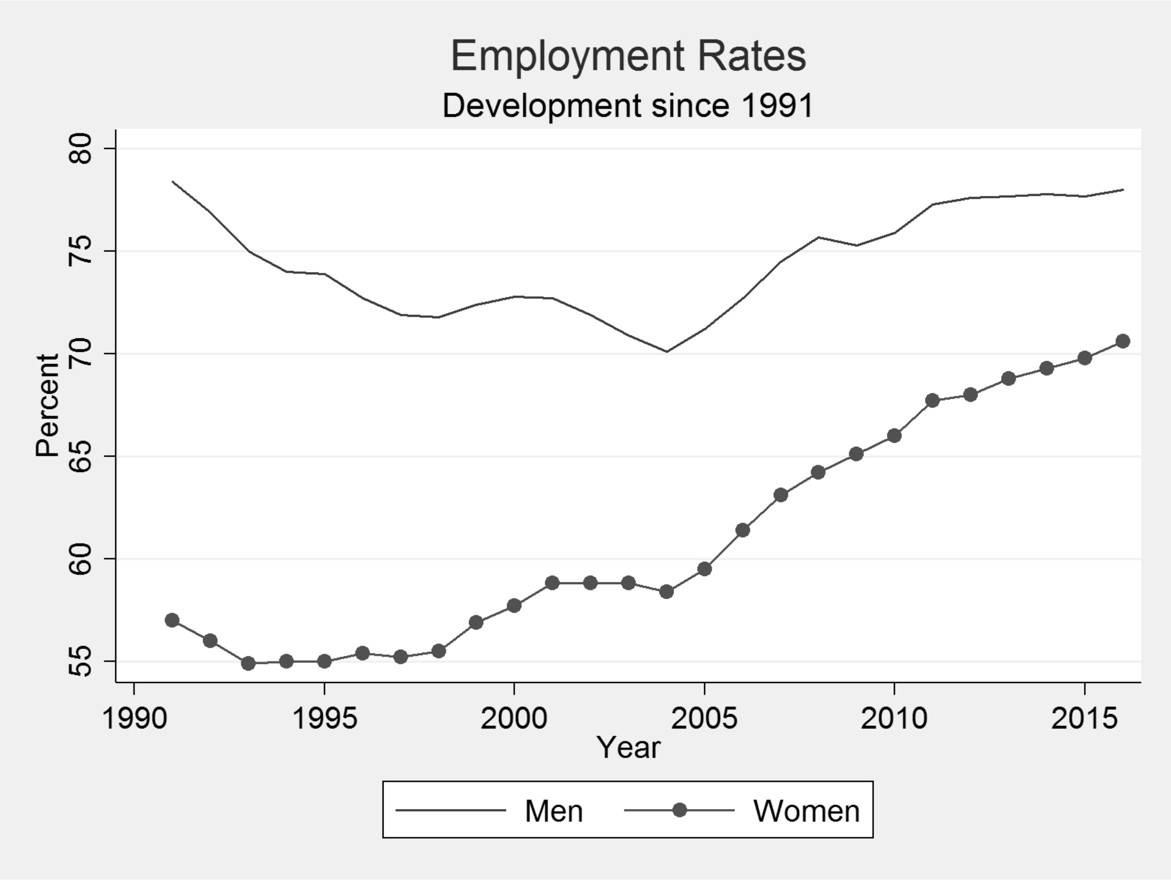
[16] see Statistisches Bundesamt: `https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/Arbeitsmarkt/Erwerbstaetigkeit/TabellenArbeitskraefteerhebung/ETQ_FB_NL_D.html` (accessed July 13, 2018)

Figure 1.2
Age-specific employment rates of men and women



Source: Statistisches Bundesamt, own calculations

Figure 1.3
Development of the age-specific employment rates between 1991 and 2016

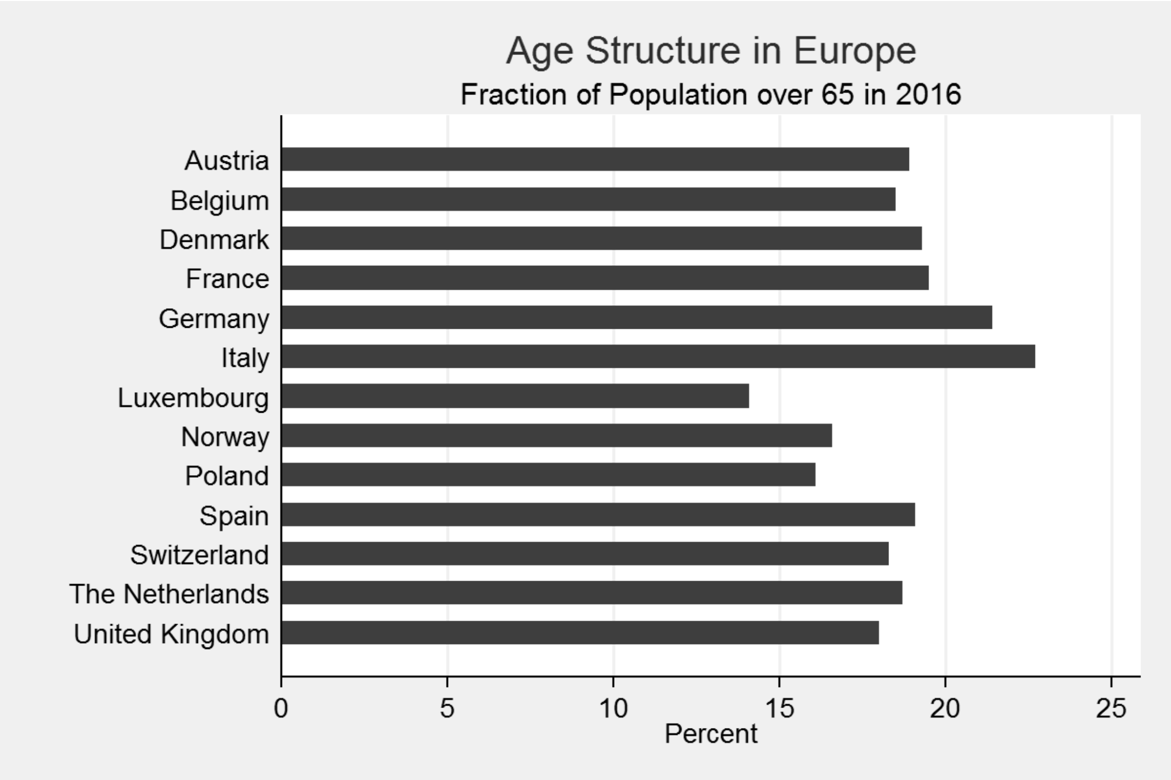


Source: Statistisches Bundesamt, own calculations

1.4.2 Demographic development

Naturally, the importance of a discussion of the gender pension gap depends of the size of the affected group. To provide insight in the relative importance of gender differences at an older age, Figure 1.4[17] compares the shares of the population over 65 for a range of European countries. It can clearly be seen from this figure that the proportion of people of over 65 in Germany is very large. In fact, this amount is only surpassed by Italy. In many neighboring countries, with Luxembourg and Poland leading the way, this fraction is substantially lower. This fact underlines the importance of the gender pension gap in Germany.

FIGURE 1.4
Share of population over 65 in European countries



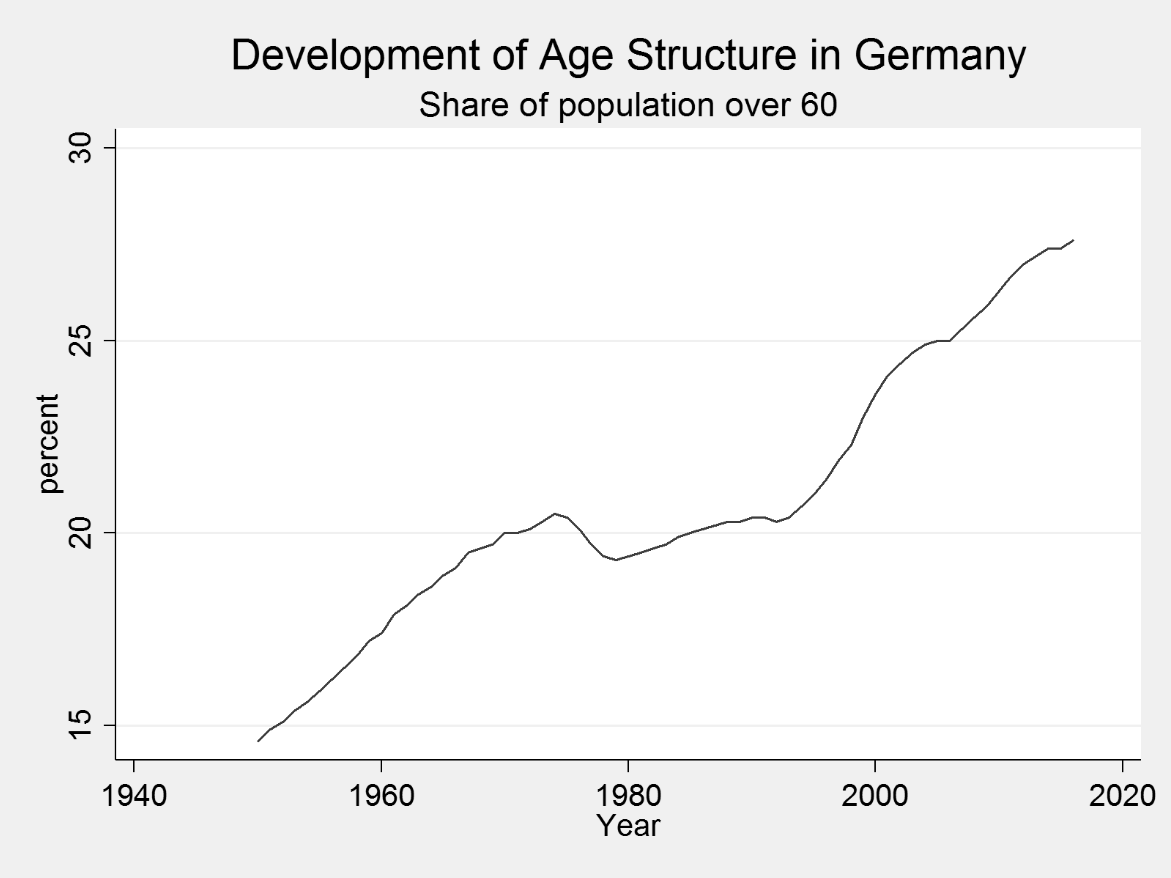
Source: Statistisches Bundesamt, own calculations

But not only the share of pensioners in the German population is large, the number of people over 60 is also increasing since the early 1950s, as Figure 1.5[18] suggests. While this amount was as large as about 15 percent in 1951, this share has increased to well over 27 percent in 2016 - in total, an increase of more than 12 percentage points and almost a doubling of this figure.

[17]see Statistisches Bundesamt: `https://www.destatis.de/DE/ZahlenFakten/LaenderRegionen/Internationales/Thema/Tabellen/Basistabelle_Bevoelkerung65.html;jsessionid=53933204A8B54DB2444FF8A144B45600.InternetLive2` (accessed July 13, 2018)

[18]see Statistisches Bundesamt: `https://www.destatis.de/DE/ZahlenFakten/GesellschaftStaat/Bevoelkerung/Bevoelkerungsstand/Tabellen_/lrbev01.html` (accessed July 13, 2018)

Figure 1.5
Development of the share of population over 65 in Germany



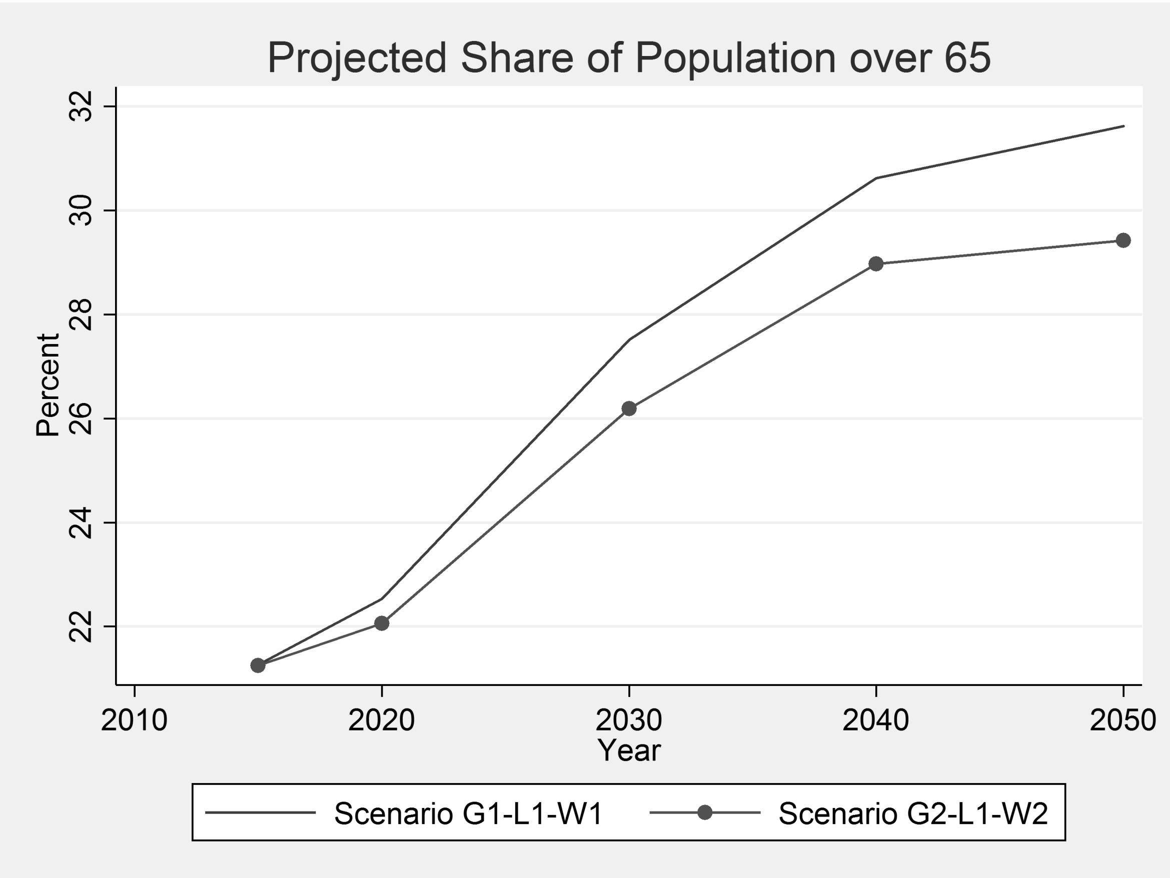
Source: Statistisches Bundesamt, own calculations

Consequently, the question arises whether this trend is expected to continue. The 2015 projection of Germany's Federal Bureau of Statistics indicates that this is, in fact, the case. Figure 1.6[19] shows two scenarios from the official population projection and the respective forecast of the share of the population over 65. Baseline scenario G1-L1-W1 projects a relatively steep decline in the overall population and a substantial aging of the German society. The assumptions of scenario G2-L1-W2 (higher fertility rates, higher net migration) lead to a slower decrease of the German population and a less significant aging effect. But still, both scenarios expect a considerable aging of the German society.

It has to be noted that some of the assumptions, even of the positive scenario (G2-L1-W2), have already been exceeded: migration figures have been substantial both in 2015 and 2016 and also fertility rates experienced a sharp incline. These factors act against a society's aging. But still, all this will most likely not be enough to stop the aging process of the German society and therefore, in

[19] see Statistisches Bundesamt: Bevölkerung Deutschlands bis 2060 - Tabellenband - Ergebnisse der 13. koordinierten Bevölkerungsvorausberechnung 2015

FIGURE 1.6
Predicted share of population over 65



Source: Statistisches Bundesamt, own calculations

all likelihood, the importance of gender differences in old-age income will continue to increase in the future underlining the importance of this topic.

Chapter 2

A Decomposition Analysis of the German Gender Pension Gap

2.1 Introduction

In Germany, the gender pension gap - the difference between the average personal pension incomes of men and women - is substantially larger than the gender difference in wages.[1] Surprisingly, this fact receives significantly less attention in recent policy discussions, even though demographic changes in aging societies like Germany lead to increased shares of people depending primarily on pension entitlements. The purpose of this chapter is to examine the current structure of the pension differences between the sexes, provide evidence which income group is especially affected, and determine the factors causing this gap.

Extending earlier work (see, for example, Frommert and Strauß (2013)), the decomposition method of Oaxaca (1973) and Blinder (1973) is used to create a detailed picture of the causes of the mean gender differences in the total old-age incomes of current German retirees. Their method is able to attribute the gender pension differences to endowment differences between the genders - like, for example, the number of employment years - and to portion that is caused by different returns to these very endowments. Going beyond the decomposition of the mean, this work also examines the causes of gender gaps for other incomes levels along the pension income distribution; specifically, it decomposes the gender pension gap for various income groups using a decomposition method for quantiles introduced by Firpo et al. (2007).

[1]This chapter is based on joint work with Jonas Klos. We thank Judith Flory, Tim Krieger, Carsten Schröder, C. Katharina Spieß, Sven Stöwhase, and seminar and conference participants at Fraunhofer FIT and at the 2014 International Institute of Public Finance congress in Lugano for their comments and discussions.

In doing so, this study is the first to use the *Alterssicherung in Deutschland* survey (ASID - see Kortmann and Halbherr (2008)) to determine the causes of the gender pension gap. Moreover, for the first time it is able to conduct a decomposition analysis for all types of pension income of the entire German population. Finally, up to this point no study exists that extends the decomposition of old-age incomes to the quantiles of a pension income distribution. This perspective is, however, important since it is unlikely that the gap and its causes are constant over the entire income distribution. This information is also relevant from a policy perspective: a gap that is mainly driven by high-income pensioners will certainly be perceived differently from one that is the result of disparities between low pension incomes.

The analysis of the ASID reveals that Germany's gender pension gap is as large as 60 percent.[2] This study shows that the main factors responsible for this substantial gap are gender disparities in the number of accumulated employment years and in the education level obtained. Those two factors alone contribute to more than two thirds of the explained gap (the part of the gap that can be attributed to endowment differences). Furthermore, it is observed that the pension income differences are particularly pronounced for retirees with little income: The gender pension gap for low quantiles of the respective pension income distributions of men and women amounts to approximately 80 percent, while this figure is as low as approximately 50 percent for pensioners that are better off. Pensioners with low income therefore distinctly drive the gap's size. But not only the size of the gap changes along the pension income distribution - the determinants of the gender differences do also vary. In particular, the consequences of the disparities in the number of employment years is a major determinant of the gap for the lower quantiles of the pension income distribution, while this effect becomes substantially smaller when pensions rise.

Old-age income from the most important pillar of the German pension system - the statutory pension scheme - is the result of accumulated entitlements in the course of a person's working life in a Bismarckian pension system such as Germany's (see, e.g., Schludi (2010)), these entitlements strongly depend on the number of employment years and the earned income.[3] Wage differences, for example, as measured in the gender pay gap, are therefore only one aspect that contributes to the gender pension gap. Hence, this study goes beyond the analysis of the wage gaps of one specific year but - due to the close relationship between pensions and lifetime earnings - examines the factors leading to the differences in income that can be accumulated during a lifetime of employment. In

[2] See also Flory (2011).
[3] See, for example, Boersch-Supan and Wilke (2004).

particular, this chapter is interested in the question which factors during an employment life lead to the observed pension gap. For this reason, wages are not included in the decomposition analysis, as it is not intended to simply recalculate the outcomes of the German pension system but to examine how individual characteristics and decisions in the course of an employment life - for example, with respect to employment or occupation - are determining the gap.

Furthermore, this study is not predominantly interested in the implications of the gender pension gap from a welfare perspective, as the differences in own pension incomes - those pension incomes that are the result of one's own paid-in contributions (as well as child rearing periods) - are first and foremost related to an individual's economic independence during old age. Only in recent years has this view received significant attention (see, e.g., the European Commission publication by Bettio et al. (2013)), suggesting an increasing general interest in the causes and consequences of gender pension differences. And, as described above, this focus on own pensions provides a direct connection with the study of lifetime employment incomes (see also Chapter 3 and 4).

Finally, the decomposition results provide first evidence about the future development of the gender pension gap. Since substantial adjustment processes between the education as well as the employment rates of men and women have taken place over the last decades (see Statistisches Bundesamt (2012) for details), one can expect that the gender pension gap will continue to decrease in the future.[4]

2.2 Previous literature

In 1973, Oaxaca (1973) introduced a decomposition method to analyze the causes of the differences in mean wages of men and women. When applying his method and using data from the Survey of Economic Opportunity, he finds, that a significant part of the wage differential can be attributed to discrimination. Jann (2008) gives a detailed summary of the methodology. Not being the focus of this study, reviewing the vast body of literature on wage decompositions that covers the various reasons for gender wage differences ranging from effects of human capital over discrimination to occupational choices is not intended.[5] Literature summaries and additional information on these issues can, for example, be found in Plantenga and Remery (2006), Blau and Kahn (2003), or Weichselbaumer and Winter-Ebmer (2005). Besides decompositions at the mean, in recent years various approaches have been developed that extend decompositions to other distribution moments. Especially for aggregate decompositions (a decomposition in an 'explained' and an 'unexplained' part - for details, see below),

[4]Quantitative results with respect to this topic are provided in Chapter 4.
[5]See, for example, Blau and Kahn (1996).

many procedures are available (for example, Juhn et al. (1993), DiNardo et al. (1996), or Mata and Machado (2005) suggest approaches that are able to capture the non-linearity of this problem). Firpo et al. (2007) provide a method that is able to conduct detailed decompositions of income distributions in the spirit of Oaxaca and Blinder. Their method uses RIF-regressions to determine the individual contributions of endowments to both - the explained and the unexplained - parts of the gap.[6] An excellent survey on methods focusing on decompositions of moments beyond the mean can be found in Fortin et al. (2011).

A descriptive introductory overview of the differences in old-age incomes between the genders within the European Union is provided by a comprehensive and recent study by Bettio et al. (2013). They observe that Germany has the second-largest gender pension gap in the entire European Union, only superseded by Luxembourg. Their study primarily uses statistics provided by Eurostat as well as the data of the EU-SILC.[7] Studies discussing the gender pension gap in Germany are, however, rare. A detailed analysis for Germany is provided by Flory (2011). Using data of the *Alterssicherung in Deutschland* survey[8], she reports that the overall gender pension gap amounted to about 60 percent in 2007. Using a data-set received from matching the Socio-Economic Panel (SOEP[9]) with the *Versicherungskontenstichprobe* (VKST[10]), Rasner (2014) compares regional differences in the gender pension gap between the former German Democratic Republic and the Federal Republic of Germany, finding that differences prevalent in 1993 had significantly diminished by 2013.

The literature on decomposition methods in the context of old-age income is also quite rare and often focused on the Beveridgean system (see Kolmar (2007)) of the United States. Johnson (1999) finds that years of job tenure and wages are the most important determinants of the pension gap in the US. Important contributions due to education or occupation are not found in this study. He explains that - when using men as reference group in the decomposition - the entire old-age income differences can be attributed to observable characteristics, meaning that there is no unexplained gap.[11] In the same year, Levine et al. (1999) use Oaxaca's decomposition method and the data of the Health and Retirement Study (HRS) to examine the nature of gender retirement differences in the United States. They estimate that approximately 85 percent of the differences in retirement income can be attributed to earnings, the number of years worked, and the choice of occupation. Also using

[6] In an application of their method based on the data of the Current Population Survey, the authors examine the causes of the co-called polarization of the labor market in the United States. They discover that this phenomenon was driven by factors such as education and de-unionization.

[7] For a comparison of EU-SILC and SOEP, see Frick and Krell (2011).

[8] Detailed information on this data-set is provided in Section 2.4.1.

[9] See Wagner et al. (2007) or Chapter 3.

[10] See also Chapter 4.

[11] The analysis is based on the data from the Health and Retirement Study.

decomposition techniques (and the data of the Current Population Survey), Even and Macpherson (2004) state that in the US the gender gap in old-age incomes has only slightly decreased. They find that differences in individual characteristics, especially with respect to salaries and experience, are the main forces causing the gap. Due to changes for women in the workforce with regard to these aspects, they expect the old-age income differences to narrow in the future. Bardasi and Jenkins (2010) use decomposition techniques on the data from the British Household Panel Survey (BHPS) to explore the differences between private pension incomes of British men and women. They discover that gender differences can mainly be attributed to lower rewards for female characteristics rather than to endowment differences. This contrasts the aforementioned findings of Even and Macpherson (2004) for the United States.

To the best of my knowledge, no study has yet conducted a detailed decomposition analysis that examines the total old-age income in Germany. Frommert and Strauß (2013) use a combination of old-age insurance and survey data (as provided by the *Altersvorsorge in Deutschland* survey (AVID)) of individuals who are currently in their working life.[12] Unlike this chapter, which focuses on personal pension incomes from all pillars of the German pension system (see also below for information on the German pension system), Frommert and Strauß (2013) project employment biographies until retirement and conduct a decomposition analysis at the mean of the resulting pension incomes. Their study is, however, limited to the West German population.

2.3 Background - the German pension system and the gender pension gap

The functionality of the German pension system as well as the idea of the gender pension gap is the key elements in this analysis of gender differences in old-age incomes. Therefore, these concepts are briefly introduced in the following section.

2.3.1 The German pension system

The German pension system in its present-day arrangement is a combination of three columns.[13] The first and by far most important column is the statutory pension plan that consists of several mandatory insurance schemes like the 'German statutory pension insurance scheme for the gainfully employed'.[14] This column has historically - since the introduction of the 'German statutory pension

[12] For details on the data source, see, for example, Heien et al. (2005).

[13] More detailed information about the German pension system can, for example, be found in Boersch-Supan and Wilke (2004).

[14] Other parts of this column are, like the pension scheme for German farmers, designed for specific groups of the German society.

insurance scheme' in 1889 - been the most important one and covers the vast majority of all German pension entitlements. The German statutory pension insurance is designed as a 'pay-as-you-go' scheme based on the principle of equivalence. This is achieved by an instrument called earning points: An employee receives one earning point per year in case of earnings amounting to the average of all incomes of employees liable to contribute to social security in this specific year. If this person earns more or less than this average, they will receive the corresponding fraction of an earning point - for instance, earning half the average will result in gaining 0.5 points. The maximum number of points that can be received per year is limited by the social security contribution ceiling, which leads to the fact that just a little more than two points can be gained in one year. After retirement, each earning point is evaluated with its current pension value. Specifically, the old-age income from the German statutory pension insurance is therefore determined as follows:

$$\text{Pension per month} = EP * PV * AF * PTF \tag{2.1}$$

EP denotes the number of earning points gained in the course of a working life. PV stands for the current pension value; an amount of money with which each earning point is evaluated. In the year 2017, each point had a value of 31.03 euros in Germany's western part, while, in East Germany, an earning point was worth 29.69 euros. With AF, an age factor which is equal to one when retiring at the statutory retirement age and lower in case of an early retirement is described. The pension type factor (above abbreviated as PTF) is determined by the type of pension which is received: in case of a regular old-age pension, this factor is one, while, for example, for pensions in case of partial invalidity it only amounts to 0.5.

Therefore, the pension in this pillar of Germany's pension system is mainly driven by the relative income position during working life and the number of years worked therein. Additional benefits for periods of bringing up children are, however, granted. For each child born after 1991, three earning points can be received by the up-bringer - for earlier born children, only one point is granted.

The second column of the German pension system consists of occupational pension schemes that are designed by employers for their respective employees. The most notable one is the additional pension scheme for the public service.[15]

The third column is formed by individual pension schemes which only recently have gained some

[15] Public service employees have the statutory pension insurance as their main source of old-age income. The occupational pension scheme is an addition.

importance due to the introduction of pension schemes supported by tax breaks or pension supplements (e.g. the so called Riester Rente) by the federal government.

Due to the historic development of the German pension system, columns two and three are still widely regarded as 'additional pensions' that supplement the statutory pension plan.

2.3.2 The gender pension gap

The gender pension gap (GPG) is designed as a measure of the differences between the average own pension incomes of men and women (see Flory (2011)). Following the lines of the so-called gender pay gap - which quantifies the inequality in earnings - the gender pension gap measures the inequality in old-age incomes as the percentage of the average female pension income in relation to the average male pension income:[16]

$$GPG = \left(1 - \frac{\text{average own pension income of women}}{\text{average own pension income of men}}\right) * 100 \tag{2.2}$$

Here and in the following discussion, only men and women with a positive own income from either pillar of the German pension system are regarded. Consequently, this analysis does not cover the entire population over 65 years. The share of people excluded from the analysis does, however, not exceed five percent of the respective age group, as only very few people do not receive payments from any pillar of the pension system (see Table 2.1).[17] Therefore, the data also provides a good representativeness of the German population over 65. In addition, only own pensions are discussed - derived pension claims are not considered as it is intended to solely capture the effects of an individual's employment history on pension income. For similar reasons, capital incomes are not considered in the analysis, as it will generally not be possible to uniquely connect those with just one partner in a married couple. Therefore, social security or welfare at an old age is not in the focus of this measure but it instead captures the economic independence that has been achieved during a working career.[18] This measure quantifies the differences in the average old-age incomes of men and women which is, to the most part, proportional to the accumulated individual lifetime earnings and as a result not only cover differences in wages but also gender specific variations in entire employment biographies.

[16]The treatment of quantiles is analogous.
[17]For a description of the data set, see Section 2.4.1.
[18]This is similar to the treatment of the gender pay gap where neither transfers among spouses nor social security payments are considered.

2.4 Data and descriptive results

The gender pension gap is calculated based on the *Alterssicherung in Deutschland* (ASID) survey - in the following section, this data set is introduced in greater detail and descriptive results on the gender pension gap and its development are presented:

2.4.1 Data

The data used in this work originates from the latest available wave of the *Alterssicherung in Deutschland* survey (old-age provision in Germany; ASID[19]) of 2007. (A detailed summary of this data set can be found in Kortmann and Halbherr (2008).) In this year, the survey was carried out for the sixth time after 1986, 1992, 1995, 1999, and 2003. Like before, it was conducted on behalf of the German Federal Ministry of Labor and Social Affairs and provides detailed cross-sectional information on the income situation of German's elderly population. Nearly 30,000 respondents over the age of 55 and younger than 80 years old as well as their spouses were asked for details about their sources of income, working life, and socio-demographic characteristics. Furthermore, the ASID wave of 2007 is the first that also includes data on private pension schemes. A more detailed description of the variables used in the decomposition is given in Section 2.6.

The ASID is the only suitable data set that provides detailed information on the composition of old age incomes as well as the previous working life. Other data sets either only focus on certain parts of the German pension system, like the data provided by the Research Data Center of the German Pension Insurance, are less detailed with respect to old-age incomes like the German Federal Statistical Office's microcensus, or that of the SOEP (German Socio-Economic Panel - see Wagner et al. (2007)) provided by the DIW (*Deutsches Institut für Wirtschaftsforschung*), contain only a fraction of the respondents in the discussed age group. A specific disadvantage of the ASID - albeit not of major importance for this study - can be found in the information on the number of children: while this information is available for all women, only married men were asked about their number of children. Consequently, no data on this matter is available for widowers.

This analysis follows Flory (2011)) in defining private old-age income as the sum of all personal claims derived from the German pension system. This includes the statutory pension plan, occupational pension schemes, as well as other individual pension schemes. Considering that the focus is on those who have reached the statutory age of retirement, persons younger than 65 are excluded.

[19] `http://www.alterssicherung-in-deutschland.de/index.html` (accessed July 13, 2018)

Furthermore, individuals without own old-age income are not examined in this study. As this chapter is interested in the root causes for differences in *own* old-age income, a person's derived pension claims - like survivor's benefits - are not included in the analysis, since those claims cannot be linked to individual contributions during the employment life (which is the main interest of this study).

Table 2.1 depicts the sex-specific shares of old-age incomes as provided by the ASID data. It can be seen that almost all men (98.2 percent) and more than 90 percent of all women receive some kind of own old-age provision. The findings for the statutory pension plan are similar; this is not surprising since the participation in this column is mandatory for many kinds of employment. Women are less likely to be employed, expressed in the lower percentage compared to men.

TABLE 2.1
Pension claims by pillar

Pension	*Men*	*Women*
Statutory Pension Plan	97.90	91.00
Occupational Pension Schemes	36.80	13.80
Individual Pension Schemes	3.10	1.50
Any Form of Old-Age Income	98.20	91.10

Source: ASID 2007, authors' calculations, (in percent of the entire population older than 65 years)

Men are also more likely to receive an income from an occupational pension schemes. This is mostly due to the fact that these are additional schemes are often provided by certain employers (for example, public service) where men were more likely to be employed in the past. Overall, individual pension schemes only have a small share, but men still benefit more frequently from these schemes than women. In the following analysis, this chapter regards old-age incomes from all three columns of the German pension system, as, in in the current chapter, the focus is on the total amount of old-age incomes and their differences between men and women.

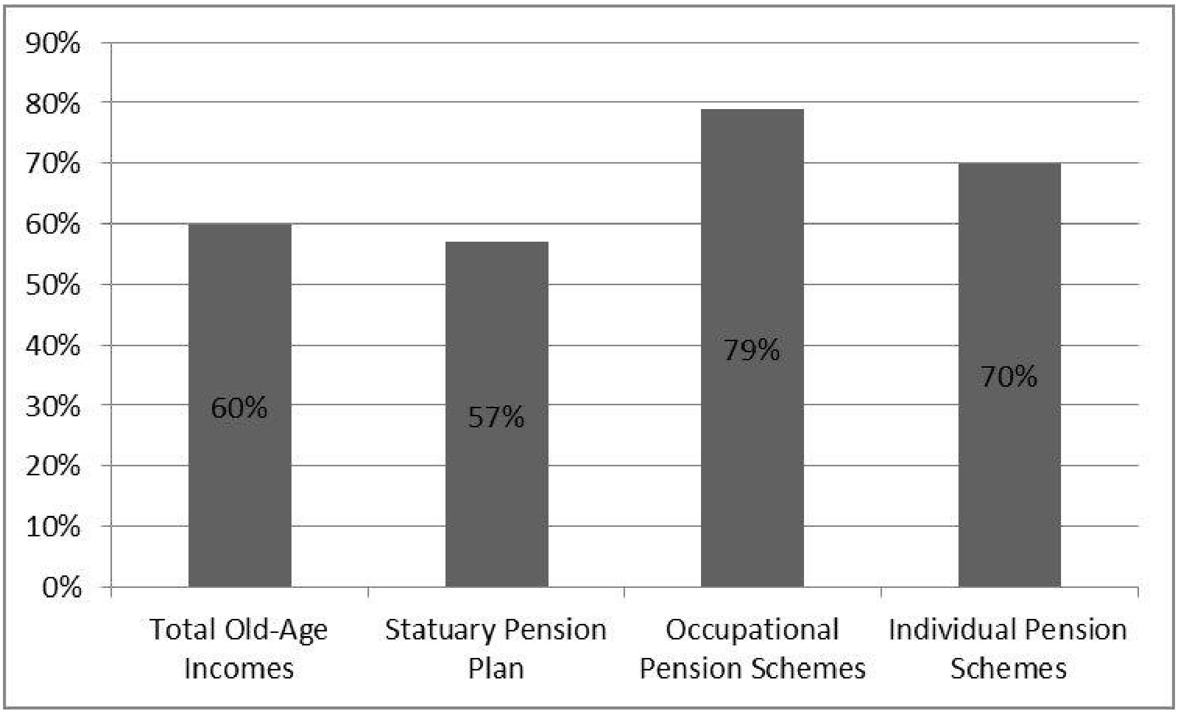
2.4.2 The gender pension gap in Germany

Applying the definitions of 2.3.2 and 2.4.1, in 2007 a gender pension gap of about 60 percent can be observed (see Figure 2.1). On average, women older than 65 receive only 40 percent of the own pension income of men. It is obvious that the gender pension gap is significantly larger than the gender pay gap estimated as 21 percent by the German Federal Statistical Agency in 2017.[20] This difference between pay and pension gap has to be expected, given that the pay gap is determined by

[20] `https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/VerdiensteArbeitskosten/VerdiensteVerdienstunterschiede/Tabellen/UGPG_01_Gebietsstand.htm` (accessed July 13, 2018)

current employment characteristics while the pension gap is influenced by employment periods in long times in the past when the wage and employment differences were far more pronounced than today.[21] Additionally, the pay gap only captures employed individuals while the development of the entire employment biography influences the pension gap. The overall gap is mostly driven by the dominant role of the statutory pension plan (the gap amounts to 57 percent in this pillar) - the gap in the second and third pillar is larger (79 and 70 percent, respectively) but these schemes play a less significant role.

FIGURE 2.1
Gender pension gap per pillar



Source: ASID 2007, authors' calculations

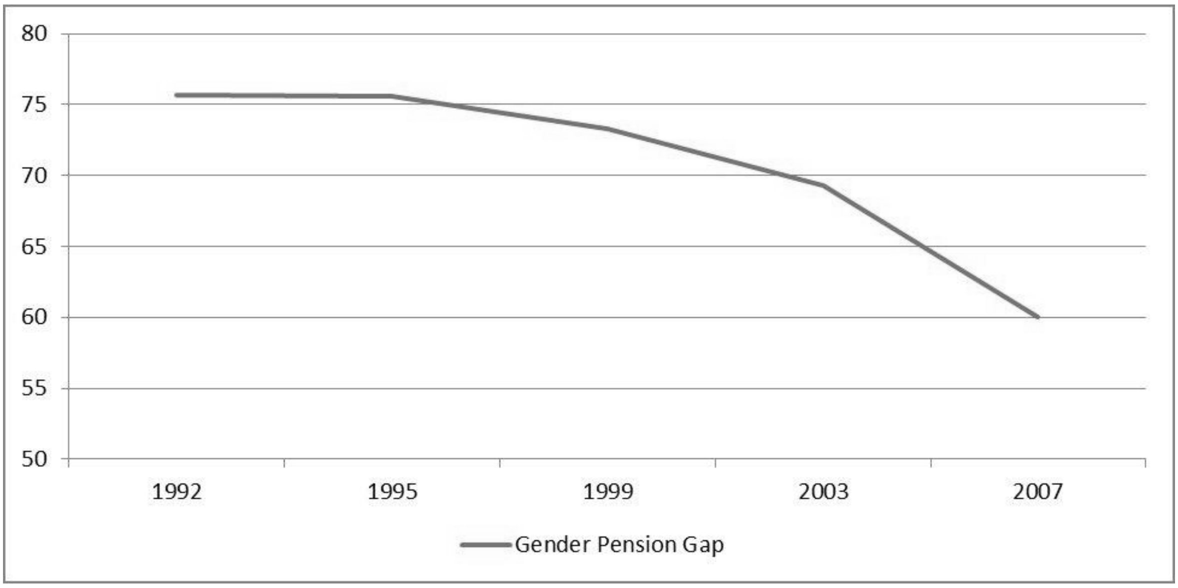
Another topic worth looking at is the development of the gender pension gap over time as shown in Figure 2.2. In addition to the discussion of the 2007 gap, this study uses the ASID waves of the years 1992, 1995, 1999, and 2003 to calculate the respective gaps. The results indicate a steady (and increasing) decrease of the gender pension gap since 1992. The gap amounted to approximately 76 percent in 1992 and declined to less than 70 percent in 2003.[22] This decline does not come as a surprise, since the qualification of women has enhanced and their labor force participation rates have increased over the course of the last decades. As increasing labor force participation rates of women

[21] Therefore, it is not surprising that the gender pension gap for the youngest pensioner cohort (aged 65 to 70) exhibits a comparatively low gap of 54 percent while this number increases in age.

[22] The age specific gender pension gap - though certainly of interest - is not discussed here. The data does, however, clearly suggest that the gender pension gap does in fact decrease for younger pensioner cohorts. Detailed results on this topics can be found in Chapter 4.

can still be observed, one might expect this development of the gap to continue in the future.[23] This is particularly the case as the effect of changing employment patterns on old-age incomes carries over slowly. Many of those who are now receiving pension incomes ended their working lives more than 20 years ago and may well have started them before the 1950s.

Figure 2.2
Gender pension gap (in percent): Development over time



Source: ASID 2007, authors' calculations

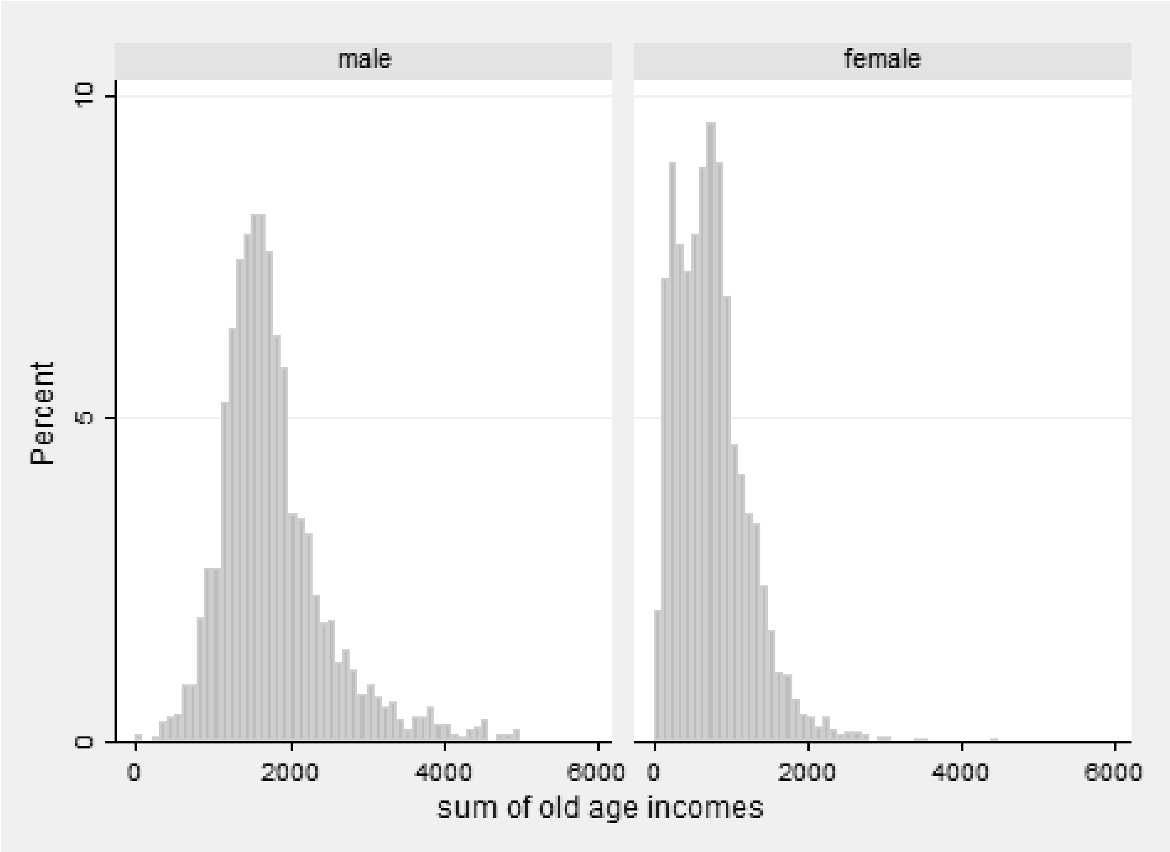
2.4.3 The gender distribution of total old-age incomes

In the following section, the study takes a closer look at the differences between the old-age income distributions of men and women (as defined in Section 2.3.2). It focuses on the variable examined using decomposition methods: the sum of an individual's entire own monthly old-age incomes from all three pillars of the German pension system. Figure 2.3 shows the distribution of the total individual old-age incomes (in euros) for both sexes.

It can be seen that the sex-specific distributions of old-age incomes are quite different. Relatively low incomes are much more common for women than for men. It can also be observed that only very few men have pension incomes of less than 500 euros while this is very common for women. This is caused by the fact that there are a significantly larger number of women with only short employment periods. On the other hand, incomes amounting to more than 2,000 Euros are not unusual for men, whereas there is almost no woman who receives such a pension.

[23]See also Chapter 4.

Figure 2.3
Distribution of old-age incomes of men and women



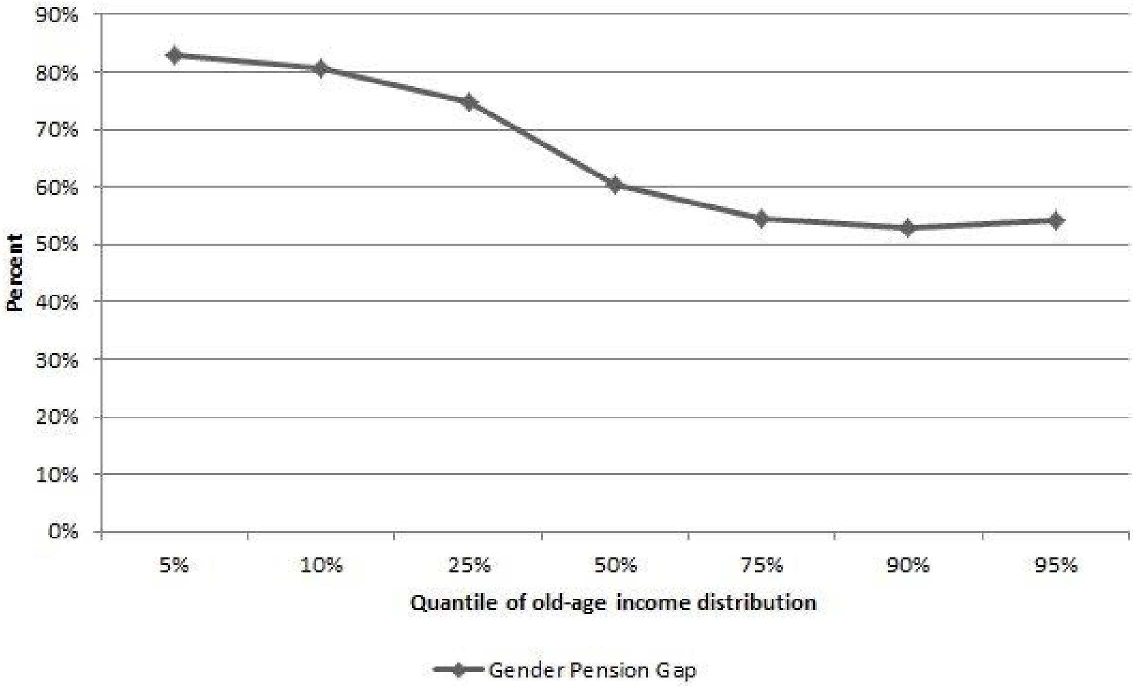
Source: ASID 2007, authors' calculations

These results suggest that the gender pension gap might not be constant over the entire old-age income distribution. Figure 2.4 shows that there is, in fact, substantial variation in the size of the gender pension gap between the quantiles of the old-age income distributions of men and women: For the lowest quantiles of the respective distributions, the gap amounts to more than 80 percent. This is due to the fact that men with a low number of employment years still have substantially more employment experience than women at the low end of their old-age income distribution. For higher quantiles, the gap steadily decreases and reaches a level of about 50 percent at the 75 percent quantile. Afterward, the gap basically stays constant. One can conclude that mainly low-income groups drive the size of the gap.

This pattern is similar to results of Fitzenberger and Kunze (2005) or Heinze (2010) for German wages; their studies suggest that the wage gap decreases for increasing quantiles of the wage distributions.[24] On the one hand, characteristics of wage distributions of men and women can certainly

[24]There is, however, no consensus with respect to this result. For example, Arulampalam et al. (2007) find a u-shaped

Figure 2.4
Gender pension gap per percentile



Source: ASID 2007, authors' calculations

translate to similar characteristics in old-age income distributions. On the other hand, particularly gender differences in the number of employment years between the sexes might well be a further major determinant of the above result. To gain additional insight in the determinants of these different gap sizes, a decomposition analysis for selected quantiles is conducted (see Section 2.6).

2.5 Decompositions methods for means and quantiles

To obtain insight into the causes of the gender differences in old-age income and to be able to attribute those to specific factors - such as education or the number of employment years - decomposition methods are very useful tools. In Section 2.4.3, it is shown that gender differences in old-age income differ across the quantiles of the income distribution. In order to see whether also the causes of the gaps differ among quantiles, decomposition methods for both the mean as well as quantiles have to be used. These two decomposition methods are described in this section: At first, the classic decomposition by Oaxaca and Blinder (Oaxaca (1973) and Blinder (1973)) is briefly reviewed. Such a decomposition of the mean pension incomes seems to be an appropriate first step and serves as the basis for further research. This chapter is the first study to provide a decomposition of the pension incomes of German retirees based on ASID data. Then, a method to decompose pension incomes at

pattern with an increasing wage gap for the higher quantiles of the income distribution.

different quantiles of its distribution by Firpo et al. (2007) is described. Their approach allows for decompositions in the spirit of Oaxaca and Blinder, but can also be applied to other moments of the pension income distribution besides the mean.

2.5.1 Oaxaca-Blinder-Decomposition of the mean

The method of Oaxaca (1973) and Blinder (1973) decomposes the mean gender gap in old-age incomes in a part caused by differences in the average endowments (for example, employment years) and in another part determined by the differences in the returns to these endowments (generally, those are referred to as the 'explained' and the 'unexplained' gap).[25] The starting point for the Oaxaca-Blinder-method are the OLS regressions of endowment vectors - for example containing education characteristics or the aforementioned number of employment years - on the (log) old-age income that are carried out for both sexes. The terms of the regression equations can be rearranged in such a way that one receives the standard two-fold decomposition:[26]

$$Gap = [\bar{X}^M - \bar{X}^F] * \beta^* + [\bar{X}^M * (\beta^M - \beta^*) + \bar{X}^F * (\beta^* - \beta^F)] \tag{2.3}$$

$\bar{X}^M$ and $\bar{X}^F$ stand for the average endowments of men and women, while β^M and β^F refer to the respective estimation coefficients of the old-age income regressions. β^* denotes an objective 'nondiscriminatory' coefficient vector. It is assumed that β^* correctly measures the revenue of an additional unit of endowment if no difference in the evaluation of endowments between the two sexes exists. It follows immediately from Equation 2.3 that the gender pension gap may arise for two different reasons: The first part of Equation 2.3 - the 'explained' part - measures the differences in average endowments evaluated in terms of the objective coefficient vector β^*. The second term measures the part of the gap that is due to deviations of the estimated coefficient from the objective coefficient vector β^*. This is referred to as the 'unexplained' part. Since β^* cannot be derived, it is necessary to assume a proxy vector (see Appendix A for the consequences of differing choices for this vector on the gap's explained and unexplained part) - following Frommert and Strauß (2013), this chapter chooses $\beta^* = \beta^M$ as the'nondiscriminatory' coefficient vector for the analysis. This leads directly to the following decomposition:

$$Gap = [\bar{X}^M - \bar{X}^F] * \beta^M + [\bar{X}^F * (\beta^M - \beta^F)] \tag{2.4}$$

[25]A comprehensive overview on the method can, for example, be found in Jann (2008).

[26]Since the regressions yield the expected gender specific incomes, the gap is given by E(*old-age income men*) - E(*old-age income women*).

Consequently, Equation 2.4 can be interpreted as follows: the explained part measures how much of the gap can be attributed to gender differences in endowments, whereas the unexplained part describes the size of the gap which results from differing returns to these endowments. Furthermore, by using $\beta^* = \beta^M$, the existence of a possible 'positive discrimination' of men is explicitly ruled out. This is done in order to gain a more focused view on the differences between the sexes.

The decomposition literature often denotes the unexplained gap as the 'discrimination component' of gender differences since it measures the differences between the gains that men and women receive from a unit of endowment. (This means that if both sexes had the same endowment vectors in Equation 2.4, there would still be a gap different from zero as long as the coefficient vectors are different.) Such an interpretation of the results should, however, be conducted with great care. Differences in the gender-specific coefficient vector that determine the size of the unexplained part, are, for example, no clear indicator for existing discrimination because the estimated gender-specific coefficients of a variable are also dependent on endowment differences (for example, economies of scale might be of influence).

2.5.2 Unconditional quantile regression

The method by Firpo et al. (2007) allows extending the methodology of Oaxaca and Blinder to additional distribution moments beyond the mean. Unlike earlier approaches (e.g., Mata and Machado (2005)), their method not only permits the quantification of the explained and the unexplained gap (the composition and the wage structure effect respectively[27]), but also is able to break these down to the contributions of individual explanatory variables. This decomposition is done in two steps: first, the entire distribution is decomposed in a wage structure and a composition effect using reweighing methods (see DiNardo et al. (1996)) and second, the contributions of the individual variables to each part of the gap are estimated using recentered influence function (RIF) regressions (see Firpo et al. (2009)).

Firpo et al. (2007) show that if the error terms of the old-age income equations of the compared groups are, conditional on the explanatory variables, independent and a common support exists, a decomposition of the form

$$Gap = (\nu_m - \nu_c) - (\nu_c - \nu_f) = \Delta_s^\nu - \Delta_x^\nu \tag{2.5}$$

[27] In line with Firpo et al. (2009), this approach sticks to their terminology when discussing the decomposition of quantiles.

is possible. In this specification, ν represents a quantile of the gender-specific old-age income distribution of men (ν_m) and women (ν_f) respectively. The counter-factual (ν_c) is received by reweighing the observations. Δ_s^ν describes the changes in the wage structure while Δ_x^ν represents the composition effect. In order to receive the counter-factual distribution, Firpo et al. (2009) define reweighing factors as

$$\omega_m(T) = \frac{T}{p},\ \omega_f(T) = \frac{1-T}{1-p},\ \omega_c(T) = \frac{p(X)}{(1-p(X_i))} * \frac{1-T}{p} \tag{2.6}$$

where $p(X_i)$ denotes the probability of being a man for given observables X_i which can be received by standard logit/probit estimation. p describes the share of men in the sample. T is an indicator, determining whether a person is a man or a woman.

Having decomposed the gap in its composition and wage structure part, the RIF regression method by Firpo et al. (2009) is applied to compute the detailed decomposition. Their recentered influence function (RIF) is defined as

$$RIF(Y_i, \nu_\tau) = \nu_\tau + \frac{\tau - \mathcal{I}_{Y \leq \tau}}{f_Y(\nu_\tau)} \tag{2.7}$$

with $\mathcal{I}_{(.)}$ denoting an indicator function that is one if the old-age income is lower than quantile τ and zero otherwise. $f_Y(.)$ is the density function of the old age incomes. Assuming linearity, standard OLS can be used to estimate

$$E[RIF(Y, \nu_\tau)|X] = X\beta_\tau \tag{2.8}$$

Due to the law of iterated expectations, $E_X[E[RIF(Y, \nu_\tau)|X]$ is equal to $E[X]\beta_\tau$. The OLS estimate of $\beta_\tau = (X'X)^{-1}X'RIF(Y, \nu_\tau)$ is in fact the marginal effect of a small change in X on the unconditional quantile. An assessable RIF function can be received by using the empirical counterparts of ν_τ and $f_Y(\nu_\tau)$ for estimation.

By combining both steps, the following wage structure and composition effects are received:

$$\hat{\Delta}_s^\tau = \bar{X}_m * (\hat{\beta}_m^\tau - \hat{\beta}_f^\tau) \tag{2.9}$$

$$\hat{\Delta}_x^\tau = (\bar{X}_m - \bar{X}_f) * \hat{\beta}_m^\tau + \hat{R}^\tau \tag{2.10}$$

where $\hat{R}^\tau$ denotes an approximation error.

2.6 Decomposition analysis

The following section describes the results of the decomposition analysis of the gender-specific old-age income differences. To goal is to determine the factors and the decisions made during an employment life that are driving these differences. At first, the variables used in the decomposition are introduced and their average gender differences are discussed - these mean differences heavily influence, as shown above in the discussion of the Oaxaca-Blinder-method, the gap's explained part in a mean decomposition. Afterward, the study presents the decomposition results for the average old-age income differences. Then, the same is done for selected quantiles of the old-age income distribution. Finally, the robustness of these finding as well as possible extensions are discussed.

It has to be noted that when examining the causes of gender pension differences, this study does certainly not intend to simply recalculate the outcomes of the German pension system. In the German pension system, wages are, as shown above, the determining factor of the number of earning points that are received in a specific year - and within the German pension system, there certainly are no 'unexplained factors'. Consequently, an inclusion of wage information in the decomposition analysis would not be a sensible decision. However, the factors that are influencing wages and biographies, such as education (see Mincer (1974)) are examined within this approach. The inclusion of the number of employment years is a more difficult choice: One the one hand, earning points can obviously only be received in employment periods and therefore are an immediate input in the pension formula. One the other hand, employment decisions clearly affect wages (see again Mincer (1974)) and future employment decisions (see Chapter 3). For these reasons, employment experience is included in the analysis of the gender pension gap.[28] Summarizing the above, it can be said that this analysis intends to detect the effects of individual characteristics - like education - and decisions made during an employment life with respect to employment, sector, or occupation on the gender pension gap. Therefore, the lifetime perspective in the generation of pension incomes and not the reconstruction of the German pension system is the focus of this study.

2.6.1 Endowment differences

Various characteristics and decisions in the course of an employment life influence gender pension differences: Most prominently, a small number of employment years will restrict the number of earning points to be gained. Also, not all sectors can be treated equally, as they can differ with respect to pay-

[28] A similar argument could be made for the inclusion of the number of working hours during the employment years - the ASID does, however, not provide this information and, additionally, the decision on the exact number of employment hours can be expected to have a smaller effect on the future employment biography than the decision whether or not to work.

ment and pension arrangements. Similar to the sectors, the occupational status[29] will affect payment and pension regulations. Furthermore, differences in education will certainly influence wages and the likelihood of an employment. The marital status is potentially linked to employment characteristics, as, for example, married women are more likely to work part-time.[30] The effect of raising children can have differing directions: On the one hand, additional earning points are granted for years of child upbringing in the German statutory pension scheme and therefore result in own pension claims. On the other hand, career interruptions will decrease the likelihood of future labor market participation and can negatively influence future wages due to human capital depreciation (see, for example, Becker (1964) and Chapter 3). Furthermore, differences between East and West Germany are included in the analysis, as statutory pension claims are evaluated at different euro amounts in East and West Germany. Additionally, women in East Germany are substantially more likely to work full-time and less likely to have career interruptions (Simonson et al. (2012)).

Table 2.2 depicts the average gender-specific endowments used in the decomposition in detail. Years of employment are given as the mean of the entire sample population and the number of children is calculated as the gender-specific average number. All other variables are given as shares of the sample population.

On average, men have about 14 years more working experience compared to women while the single most important difference can be found in the number of employment years in the private sector. Men were on average employed more than 30 years in this sector while this value is less than 20 years for women. Differences in the other sectors are not as pronounced with women having slightly more employment years in the public sector. As expected, the share of women with one or more breaks in their employment career is considerably larger than that of men. The percentage of women that has never worked is larger than that of men, though this proportion is small for both men and women.

With respect to the occupational status, two major differences between the sexes can be found: women work more likely as employees than men, while the civil service was a predominantly male sector. Interestingly, the percentage of women and men stating to have been workers for most of their employment lives is equal. Furthermore, the data illustrates the substantial gap in past qualifications between men and women.[31] While about 50 percent of men and women received a vocational training, there is a huge disparity in the shares of those who received no training at all: 13 percent for male

[29] The status refers to the main type of occupational status during professional life.
[30] See Franz (2011).
[31] The ASID data contains information on education in four ISCED-categories.

Table 2.2
Endowment differences between men and women

Variable	*Average Endowment Men*	*Average Endowment Women*	*Differences*
Years of Employment: Self-Employed	3.69	2.66	1.03
Years of Employment: Private Industry	30.12	19.02	11.10
Years of Employment: Public Service	4.95	5.29	-0.34
Years of Employment: Civil Service	3.27	0.54	2.73
Non-continuous Employment-History	0.03	0.47	-0.44
Has Never Been Employed	0.003	0.01	0.00
Worker	0.41	0.40	0.01
Employee	0.40	0.51	-0.11
Civil Servant	0.09	0.02	0.07
Self-Employed	0.10	0.07	0.03
No Training	0.13	0.40	-0.27
Occupational Training	0.51	0.47	0.05
Master Craftsperson, Polytechnics	0.21	0.04	0.17
University	0.09	0.03	0.06
Miscellaneous Training	0.06	0.05	0.00
Married	0.76	0.45	0.32
Widowed	0.13	0.41	-0.28
Divorced	0.06	0.07	-0.02
Single	0.05	0.07	-0.02
Children	1.57	2.03	-0.47
Region	0.20	0.22	-0.03

Source: ASID 2007, authors' calculations

but 40 percent for female pensioners. A similar picture can be found for the highest qualification level - only 3 percent of all women in the sample possessed a university degree while 9 percent of the men received this qualification.

The differences in the marital status mainly arise due to disparities in life expectancy. Since women tend to live longer than their partners, they are more likely to be widowed. Single or divorced men and women only play a minor role in the sample. The disparity in the number of children is basically an artifact of the ASID's questionnaire design since only married men were asked whether they have children (see also Section 2.4.1). Here, the number of children for men without information was set to zero.

2.6.2 Results of the decomposition at the mean

When applying the Oaxaca-Blinder decomposition and using men as reference category, an explained gap of 26 percent can be found, while the remaining 74 percent cannot be explained by endowment effects.[32,33] The relative largeness over the unexplained gap should, however, not be over-interpreted. The composition of explained and unexplained gap is volatile and highly dependent on

[32]For categorical variables, this study applies the normalization procedure described in Jann (2008).

[33]Detailed results of the decomposition can be found as well as the underlying regression estimates can be found in Table A.1,Table A.2, and Table A.3 in Appendix A.

the chosen reference category (see also Section 2.5 and Appendix A). Table 2.3 shows how much each variable contributes (in percent) to the explained and unexplained parts of the gap. The results of the underlying regressions are presented in detail in Appendix A. In the following the major findings of this analysis are discussed.

Two factors mainly contribute to the explained gap: the number of employment years and education. Due to the design of the German pension system's first and most important pillar, each year of employment will lead to an additional revenue in pension incomes. As can be seen in Table 2.2 that men were employed for a considerably larger number of years, the importance of this aspect does not come as a surprise. Disparities in education also play a major role in determining the explained gap, because they directly affect the value of employment years by influencing wages.[34]

TABLE 2.3
Decomposition based gap contributions (in %)

Variable	*Contribution to Explained Part*	*Contribution to Unexplained Part*
Years of Employment: Self-Employed	-2.39	-4.14
Years of Employment: Private Industry	41.45	-44.94
Years of Employment: Public Service	-1.48	-15.15
Years of Employment: Civil Service	21.00	-1.57
Noncontinuous Employment-History	12.55	6.73
Has Never Been Employed	0.04	0.11
Worker	-0.32	-1.41
Employee	-5.13	4.74
Civil Servant	2.73	-0.65
Self-Employed	-0.83	0.75
No Training	18.49	1.00
Occupational Training	-1.66	1.26
Master Craftsperson, Polytechnics	0.28	-0.42
University	6.47	0.20
Miscellaneous Training	-0.03	-0.06
Married	12.47	14.90
Widowed	-9.10	14.82
Divorced	1.01	-3.06
Single	0.30	-1.98
Children	0.80	-6.52
Region	3.34	-7.42
Constant	-	142.82

Source: ASID 2007, authors' calculations

Overall, the differences in employment years are the cause of nearly 60 percent of the gap's explained part. Due to the importance of the private sector and the substantial differences in average employment years between the sexes, employment years in the private industry alone contribute to more than 40 percent of this part of the gap. The second largest disparity in employment years can

[34]See, for example, Mincer (1974).

be found in the civil sector; this directly translates, with about 20 percent, to the second largest contribution to the gap's explained part. Due to the comparatively little significance and only small endowment differences, self-employment and the civil service sector play only a minor role in explaining the gap. The higher number of career interruptions of women can be attributed to another 13 percent of this part of the gap, though a significant effect of this variable cannot be found. As education influences wages and consequently pensions, differences in qualification significantly contribute to the gap. In total, almost 25 percent of the explained gap can be attributed to disparities in education. Most prominently, the larger fraction of women without any training leads to an increase of about 20 percent in this part of the gap. Furthermore, the higher share of men with a university degree also accounts for a sizable - albeit lesser - part of the gap. The effect of the occupational status is relatively small. The largest contribution can be found for the status of being an employee that is explaining roughly 5 percent. Due to a higher share of married men compared to married women, one receives an increase in the gap of about 12 percent. This effect is basically mirrored for widowed sample members. The effect of the remaining explanatory variables is only marginal.

It is therefore immediately apparent that a continuous employment biography and education are the main factors guaranteeing economic independence at an older age and are, vice versa, the factors leading to the substantial gap in old-age income. Gender roles in employment and education, mostly of times long past, have led to a pension gap of about 60 percent. The increased labor force participation rates of women over the past decades lead to the expectation that the gap will continue to shrink further in the future. Looking at the youngest cohort of retirees (aged between 65 and 70), this analysis does indeed find that their gap is smaller than the gap of older cohorts. The development in education shows a similar pattern. Unlike in the past eras determining the pension gap, today the qualifications structures of men and women are very much alike. A concern with respect to the steady decrease of the gap might, however, lie in the increase of part-time work (most prominently in the so called 'mini-job'- see also Chapter 4), especially for women. Certainly, the closing of the pension gap is a slow process as the changes in qualification and employment are themselves only slowly developing over the last decades. And it is also certain that the pension gap will not close entirely in the foreseeable future as the pay gap is still substantial.

The interpretation of the gap's unexplained part is not as straightforward. While the explained part is composed of the different endowment effects, the unexplained part can be seen as the result of an unspecific difference, represented by the gap in the regression constants, that is successively reduced by the included variables. This unspecific, constant-related, difference represents those influences that cannot be attributed to the variables included in the decomposition. Discrimination might be one factor in this unspecific difference, but other causes, like for example differences in preferences will also be of significant importance. Employment years in the private sector are again the most important influence in counteracting the large unexplained gap due to the difference in constants. Other types of employment years do also have a decreasing effect on the unexplained gap. The fact that higher coefficients of employment years for women than for men[35] can be found may be unexpected at first but could be caused by two effects: Firstly, economies of scale might cause that the average increase in wages (and therefore pension income) is smaller for men compared to women as on average, men worked for a substantially longer period of time. An additional year might therefore have smaller effects. Secondly, since the log-level specification measures the relative increase of pension incomes, the estimated effect size for women may be larger than in absolute terms because of women's (on average) lower endowments. This effect can therefore be interpreted as follows: each year of female employment will in fact decrease the gap in the average difference of old-age incomes. This counteracts to a certain degree the fact that the differences in endowments of employment years are a main determining factor for the size of the explained gap. In contrast to employment years, education, which was of importance in the explained part, has only a minor (and for most categories insignificant) effect, suggesting no large difference in the return on education.

2.6.3 Results for the quantile decomposition

Using unconditional quantile regressions, the decomposition of the previous section is extended in order to examine different parts of the gender-specific (log) old-age income distribution. This allows to gain additional insight not only into whether the composition of the gap in explained and unexplained parts is constant over the pension income distribution but also if the factors determining the gap are varying. This section therefore takes a closer look at the gap and its division into explained and unexplained parts. (Results of quantile decompositions at the 10, 25, 50, 75, and 90 percent quantiles are shown in Appendix A.[36])

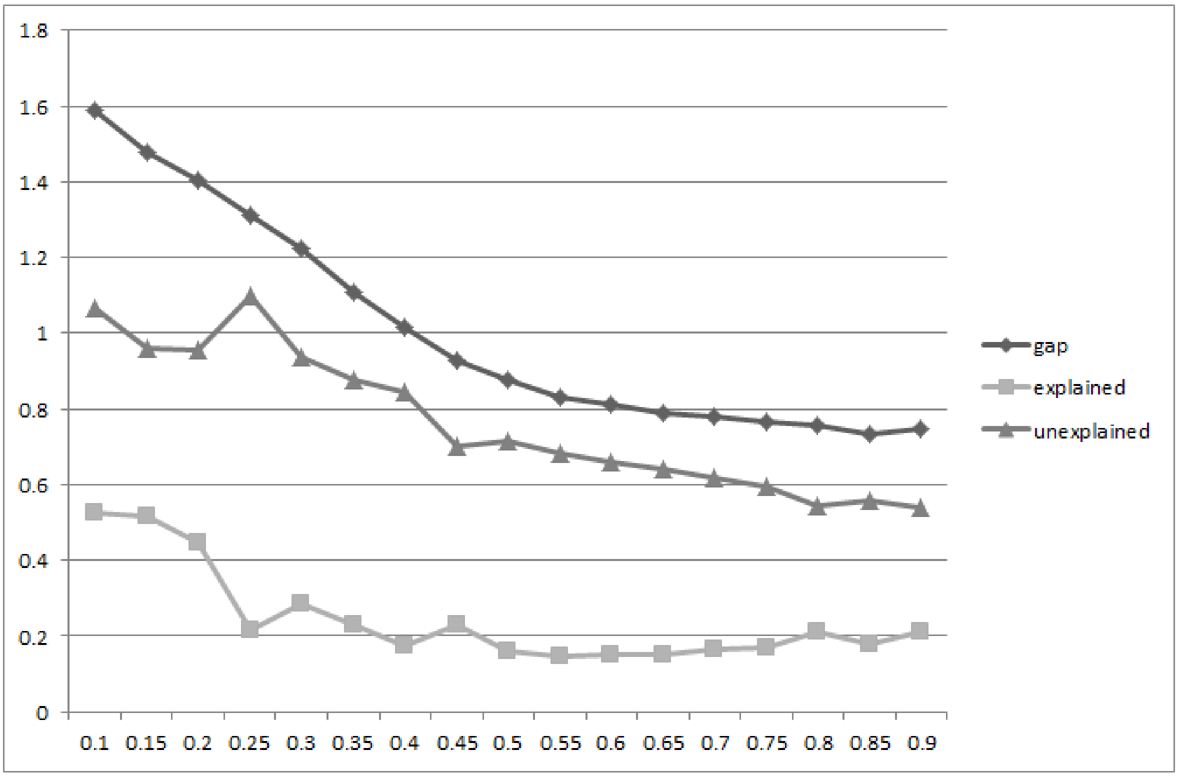
Figure 2.5 depicts the absolute log old-age incomes differences and their composition in explained and unexplained part for different quantiles. Similar to the results shown in Figure 2.4 (depicting the gender pension gap as the relative difference between old-age incomes of men and women; see Section 2.3.2), the study finds a decreasing gap, particularly below the median. (Only at the highest quantile,

[35] Negative sign of the gap contributions (gender specific coefficients are shown in Appendix A).

[36] Detailed results of the decomposition can be found as well as the underlying regression estimates can be found for the 10 percent quantile in Table A.4,Table A.5, and Table A.6, for the 25 percent quantile in Table A.7,Table A.8, and Table A.9, for the 50 percent quantile in Table A.10,Table A.11, and Table A.12,for the 75 percent quantile in Table A.13,Table A.14, and Table A.15, and, finally, for the 90 percent quantile in Table A.16,Table A.17, and Table A.18.

a slight increase in the gap is visible.) It can further be seen that the pension inequality is especially large for low-income groups. The decrease is primarily driven by a reduction in the unexplained part while the explained difference remains relatively stable above the 25 percent quantile. Figure 2.5 shows that differences in endowments are more important for the lowest quarter of the distribution while for higher quantiles the gap reduction is mainly due to the smaller differences between male and female returns.

FIGURE 2.5
Gaps per quantile



Source: ASID 2007, authors' calculations

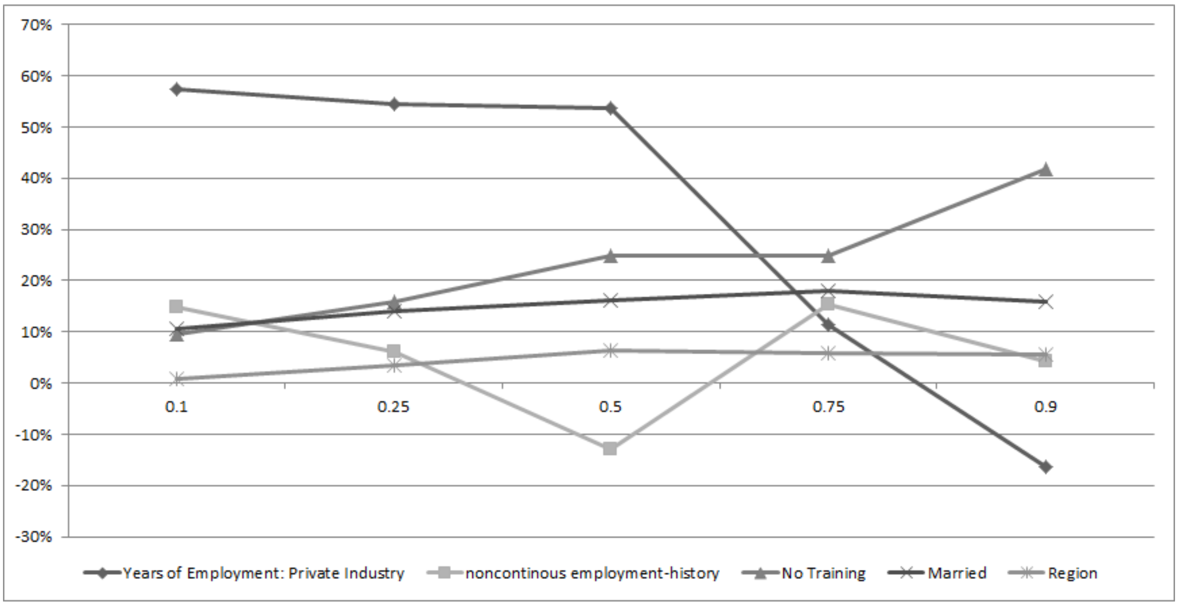
Figure 2.6 shows the quantile-wise contributions of the most important variables on the explained part of the gap. Years in the private industry account for nearly 60 percent of the explained part at the 10 percent quantile and still for over 50 percent at the 50 percent quantile. For higher incomes, the contribution of the employment years in private industry drops heavily and is of substantially less significance. This is partly due to the fact that in the low quantiles there are women whose own pension claims originate in large part from child-rearing times. However, it is also important to note that the effect of child rearing times as sole contribution to the own pension claims on the gap and its decomposition should not be overestimated, given that only 11 percent of all women in the sample (and four percent of the men) state to have no employment experience at all. The effect of the employment years in the civil sector is always positive along the entire distribution. After controlling for the number of employment years, a non-continuous employment history does not have a significant effect.

Having no training is of increasing importance across the distribution. At the 10 percent quantile, it accounts for over 10 percent of the explained part, while at the 90 percent quantile it determines over 40 percent of the explained part. Similarly, a university degree contributes the most to the explained gap for the highest quantile.

The effect of being married is quite stable across the distribution, which hints at the fact that male benefits from being married are independent of the position in the distribution of old-age incomes. Living in Eastern Germany is of little importance in terms of gap contribution in the lower parts of the distribution while the analysis finds an increasing effect on the explained part for higher quantiles.

The results show that increased labor force participation of women - especially a shrinking number of women with only short or no employment spells - should massively reduce the gap for the lower quantiles (where the gap is the largest) and therefore also significantly reduce the overall gap. In the higher quantiles, qualification effects are expected to close the gap substantially, as, of now, the differences in qualification between men and women have diminished.

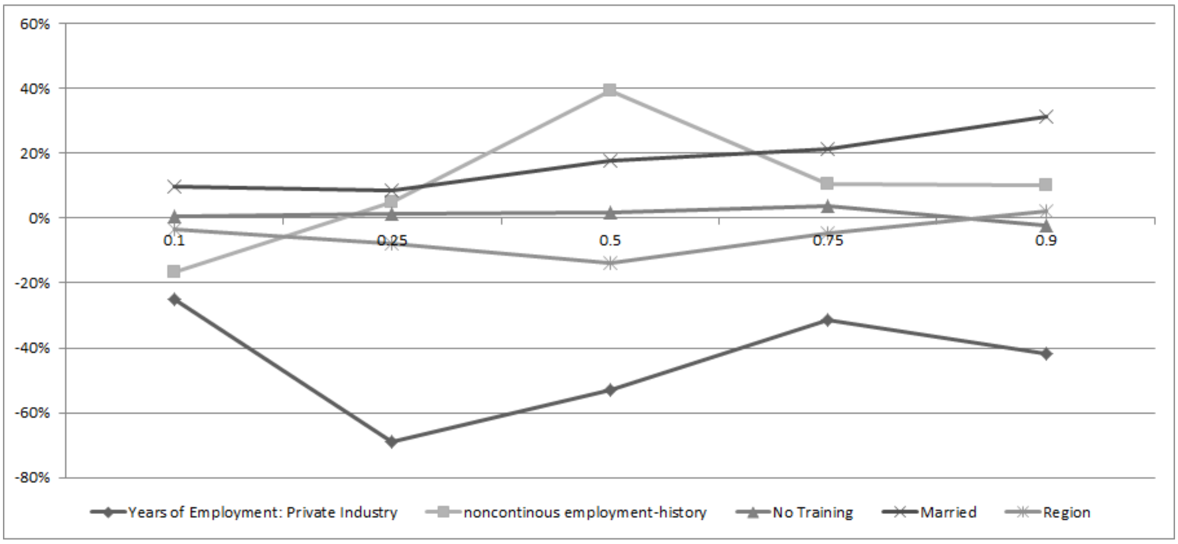
Figure 2.6
Explained effect per quantile



Source: ASID 2007, authors' calculations

Similar to the mean decomposition, the unexplained gap is mainly driven by differences in constants. As well as in the decomposition of the mean, the coefficient estimators for the effects of an additional year of employment in the private industry at each quantile are larger for women than for men, resulting in the largest contribution of this variable in reducing the unexplained gap (see Figure 2.7). This difference in returns tends to be smaller for higher quantiles of the pension income distribution (which is in line with the presumption that these differences originate in scale effects). A non-continuous employment history has gap-reducing effects on the 10 percent quantile but increases the unexplained part above the 25 percent quantile, whereas having no training has only little influence. Being married leads to higher returns for men across the distribution with slightly more distinct effects for higher quantiles. The graph for the regional variable shows that living in Eastern Germany has less severe effects for women below the 90 percent quantile. At the 90 percent quantile differences in the effects of the region are nearly nonexistent and insignificant.

FIGURE 2.7
Unexplained effect per quantile



Source: ASID 2007, authors' calculations

2.6.4 Robustness

In the literature on wage decompositions, selection biases related to employment are a constant concern. In general, the correction approach of Heckman (1979) is used to control for selection - but finding valid exclusion restrictions often pose some difficulties. In the context of old-age incomes in Germany, selection is far less of a concern, as nearly every retiree (almost all men and more than 91 percent of the women, see Table 2.1) receives an income from a pillar of the German pension system. The reason, to a certain degree, is that the Statutory Pension Insurance awards pension entitlements unrelated to employment - entitlements resulting from raising children would be one example. The study therefore refrains from using a correction for potential selection.

Potential further biases might arise due to differences in the dropout behavior out of the sample (longer life expectancy of women, potentially longer life expectancy for retirees with high income). Therefore, the analysis was replicated for the youngest age group in the sample (65 to 70) for which mortality rates are comparatively low. As expected, the overall gap slightly decreases, the other major findings do, however, not change. Similarly, including or not including the age as an independent variable does not alter the result in any considerable way.

The size of the gap's explained and unexplained parts strongly depend on the choice of the reference group, with the explained part of the gap being the lowest for the chosen specification. The relative importance of the major factors influencing the gap and its parts are, however, not affected. For further details on the effects of the reference group choice, see Appendix A.

2.7 Conclusion

This chapter extends earlier work in providing a detailed discussion of the differences in all own pension incomes from all three pillars of the German pension system for current old-age pensioners. It is the first to provide descriptive and decomposition based results for quantiles of the old-age income distribution of German retirees and examines the determinants of the gender pension gap in Germany. It describes how this gap and its determinants differ along the pension income distributions of men and women. It thereby also provides insight on how the gender pension gap is likely to develop in the future and on how policies can affect the gap.

Using ASID data, it is observed that the German gender pension gap amounts to approximately 60 percent. Applying the Oaxaca-Blinder decomposition, this analysis finds that a substantial fraction of the gap cannot, at least not within specifications possible with ASID data, be explained solely by differences in endowments. The explained part of the gap is heavily influenced by two categories of variables - employment years, especially in the private sector, and education. The number of employment years is the most important variable in the unexplained part of the gap, while education is of less significance. The gap's size is mainly driven by the low quantiles of the pension income distribution. The differences in these quantiles are primarily explained by the numbers of employment years. Education is of greater importance in the higher quantiles. Taking into account that the gap is dominated by lower quantiles, an increase in female labor force participation will result in a more pronounced reduction of the gap. As this increase can actually be observed over the last decades [37], one can expect that these differences will indeed lose some importance and the gap will further close in the future. The finding that employment years in the private sector are the single most important endowment explaining the gap is shared with a previous related study for Germany (see Frommert and Strauß (2013)). One can, however, observe a larger effect of education in explaining the gap than the previous literature, which might be due to the fact that these studies examine younger cohorts for which disparities in education have already diminished. Similar to female participation rates, major improvements in education can be found in the course of the last decades. The qualifications of men and women are now very similar, with slight advantages for women.[38] Consequently, this development should lead to a reduced explained gap for future cohorts of pension beneficiaries. Summarizing, it can be concluded that the homogenization of education will specifically close the gap for women with higher pension income, while the improved employment rates will be particularly beneficial at lower quantiles resulting in a steady overall decrease of the gap.

From a policy perspective, any attempt to close the gender pension gap by influencing the gap's determinants in the short run would be in vain as the gap will (for a substantial number of years in the future) reflect past social conditions and policies.[39] However, this analysis shows that a policy enabling increased labor force participation of women will be successful in decreasing the gap[40] - especially due to the pronounced size of gender differences in the lower pension income quantiles. It has to be emphasized that full-time employment would be the most preferred means of reducing the gap due to the linkage between employment and paid contributions in the statutory pension plan. Policies have already been adopted that aim to encourage increased employment of women. For example, since 2013 it is possible to file a legal claim to obtain a childcare slot for children under the age of three. A similar claim for older preschool children was established as early as 1996. These schemes should be - and already have been - able to encourage employment of mothers[41] and thereby reduce the gender pension gap.

One step forward for future research would be decomposition into cohorts within the latest version of the ASID data. This proceeding would allow for a detailed analysis on gap and decomposition development and the effects of changes in employment on both. Furthermore, a prediction of the future

[37] See Statistisches Bundesamt (2012).
[38] See Bildungsberichterstattung (2012).
[39] Though, at least in principle, the gap could be closed by a substantial subsidization of the old-age incomes of women.
[40] Such a policy would certainly also help to reduce the gender differences in wages.
[41] See, for example, Büchel and Spieß (2002).

gap in pensions could be carried out using these results and micro-simulation models of employment biographies.

Chapter 3

Long-run Effects of Career Interruptions - A Micro-simulation Study

3.1 Introduction

During the course of a working life, interruptions of employment tend to be the rule rather than the exception, even though duration and frequency as well as causes are highly heterogeneous in a society like Germany.[1] In particular, men and women exhibit distinctly different interruption patterns - it is particularly the case that women tend to interrupt their careers for longer periods than men, for example when raising children. While it is well known that such career interruptions have a lasting, though diminishing, negative impact on wages after reentry, much less is known about the size and the timing of these costs and on how the length of an interruption influences reentry in the first place. Career interruptions affect the entire future career path as employment and wages will be heavily influenced by, for example, employment experience in the long run. There are, however, to the best of my knowledge, no studies that quantify the lifetime cost of career of an average career interruption. This analysis for Germany fills this gap and thereby provides policy makers with an improved evaluation tool to assess the total effect of policies encouraging employment and gives those considering to extent an interruption concrete additional information to base their decision on. The situation in Germany is of particular interest as, for many years, German women interrupted their employment for remarkably long periods (see, for example, Gutierrez-Domenech (2004)) - a condition that has only mitigated in recent years (Statistisches Bundesamt (2016c)).

[1]This chapter is based on joint work with Jonas Klos. We thank Daniel Reck, Carsten Schröder, C. Katharina Spieß, Sven Stöwhase, Katharina Wrohlich, and seminar and conference participants at Fraunhofer FIT, the University of Freiburg, the guest lecture at the Bamberg Graduate School of Social Sciences (BAGSS), and at the 2016 International Institute of Public Finance congress in Lake Tahoe for their comments and discussions.

Previous studies either empirically estimate the average effects of a career interruption or use micro-simulation to quantify the life-time consequences of policy changes. Spivey (2005), for example, uses US Panel data (National Longitudinal Survey of Youth) to show that the effects of career interruptions are still detectable long after a reentry. Geyer and Steiner (2014) simulate the effects of variations in employment patterns on pension income - the discussion of pension income is closely related to the content of this study as life-time income and pension are closely related due to the design of the German pension system (see also Chapter 2). This chapter contributes to the literature by combining empirical methods for the analysis of interruptions with micro-simulation and hence provides a tool (using German micro-data) to quantify the cost of a career interruption on the individual as well as the society level. The resulting model allows the evaluation of the timing of these cost for individual biographies, providing much more detailed results than purely relying on econometric estimation methods could as it not only provides estimators of average effect sizes but predicts an individual employment path for each person in the sample. Furthermore, the simulation is able to capture existing trends of social change (like the proceeding increase of women's labor force participation - see Chapter 1) and therefore allows better predictions. The model does not only calculate the cost of an employment break on an individual level, it also aggregates the results for the entire society.

The determinants of changes in employment status, working hours and wages are estimated using data of the German Socio-Economic Panel (SOEP).[2] Based on these estimation results as well as information on the completed part of the employment biography, the study predicts each individual's employment path until retirement. In counter-factual simulations, it is therefore able to quantify the effects of changes in interruption length and timing. In doing so Chapter 3 assesses the lifetime effect of employment breaks. This analysis is also carried out for subgroups divided by sex and age. Specifically, the simulations suggest that an interruption's long-term consequences are, in spite of (slowly) diminishing effect sizes, substantial: the study shows that as much as 40 percent of the average total interruption cost can occur in the second half of the time period between reentry and retirement. This is due to the long-term effects of human capital loss such as constantly lower employment experience resulting in lower wages and an increased likelihood to end an employment. These findings underline the significance of the lifetime perspective when discussing the effects of career interruptions.

This lifetime perspective and the possibility to evaluate effect sizes allows the gathering of additional insight not only into the life-time consequences of employment breaks but also, due to the close connection between old-age and lifetime income in the German pension system, into its influence

[2]For information on the SOEP, see, for example, Wagner et al. (2007).

on old-age income. Thereby, this study also contributes to the ongoing discussion on poverty among the elderly (see, for example, Goebel and Grabka (2011)) as well as that on the development of the gender differences in old-age income ('gender pension gap', see, for example, Hänisch and Klos (2014)).

3.2 Previous literature

This paper draws from two strands of economic literature - that on the simulation of life-time earnings (often in the context of pension reforms) as well as that on the effects of career interruptions. The following section provides a brief overview of both:

Since Mincer's influential work on the relations between education, experience, and earnings (Mincer (1974)), a vast amount of research on the effects of employment histories on income has been conducted. Interruptions in employment histories are likely to influence individual earnings because of manifold reasons: Mincer and Polachek (1974a), Mincer and Ofek (1982), or Light and Ureta (1995), for example, extend Mincers work by taking human capital depreciation due to skill loss as a consequence of reduced experience and not keeping up with new relevant developments into account which can lead to lower wages at re-entry. Furthermore, it is possible that a catch-up effect of wages after reentry can counteract the consequences of human capital depreciation in terms of lowered wages over time, even though the timing and amount of catch-up is highly case dependent (see, for example, Licht and Steiner (1992)). Expanding on the question of timing, later studies on interruptions investigated if earnings are not just affected by the most recent career interruptions, but also by those with a significant time lag. Spivey (2005) uses longitudinal data of men and women from the United States - the National Longitudinal Survey of Youth - to investigate if there is a difference between past and more recent interruptions regarding the effect on earnings. She finds that although recent interruptions are of importance, past interruptions, even at the beginning of a working life, do still matter, especially for women.

Using Mincer-style wage equations[3] in a two step procedure following Heckman[4], Boll (2011b) examines the panel data of the German Socio-Economic Panel (SOEP) to quantify the forgone gross earning of stylized interruption patterns due to child birth for West German mothers. She finds that women suffer significant losses in terms of wages and accumulated earnings. Ejrnaes and Kunze (2013) further discuss the effect of first childbirth on women in the West German labor market in a fixed effects estimation approach based the data of the IAB employment sample (IABS[5]). They come

[3]See, for example, Mincer and Polachek (1974b).
[4]See Heckman (1977).
[5]See Bender et al. (2000).

to the conclusion that women with large wage losses due to childbirth are more likely to return to full-time employment while returns to experience are lower after childbirth in comparison to those of women without children. It has to be noted that these findings have their focus on the situation in Germany. Results may vary depending on which country is focus of a study. As an example, Gupta and Smith (2002) use panel data to investigate the effect of career interruption on women's earnings in Denmark. Also contrary to similar studies in the United Kingdom (see Gangl and Ziefle (2009)) or the United States (see also Spivey (2005)), they come to the result that in Denmark, children do not negatively affect the mother's wage. Boll and Beblo (2014) expand on the topic of child induced career interruptions by looking at the conflicts of interest of couples. Mothers are believed feel obliged to give up their employment after childbirth due to the asymmetric dynamic of a couple, even if she is aware of the significant threat to the material security she might face.

Micro-simulation models have manifold applications and a long tradition - for example, Orcutt et al. (1986) provide an overview on the application of such models in social and financial policy. In a more recent contribution, O'Donoghue et al. (2009) describe a generalized framework for dynamic micro-simulation models that can be used as a guideline for constructing these models. It provides insight in the methodology of dynamic simulation models and how modularization and dynamization can be implemented. Another detailed overview of the methodology of dynamic simulation models can be found in Favreault and Smith (2004) - their 'dynamic simulation of income model' is used to simulate how changes in social security legislation affect future retirement benefits of various socio-demographic groups. Their study uses the data of Survey of Income and Program Participation (SIPP[6]) and of the Panel Study of Income Dynamics (PSID[7]) as primary data sources.

Only a small number of studies employ micro-simulation models to predict employment biographies in the context of life cycle and retirement. Lemieux (2006) use an agent-based discrete choice micro-simulation model to investigate the effects of an aging society on labor supply in Italy. They find that an expected sharp decline in labor supply due to rapid population aging and low participation rates can be offset by recent reforms in retirement legislation as well as changes in education and the participation behavior of future retirees. Michaud and Rohwedder (2008) employ a dynamic simulation model to forecast retirement patterns and old-age incomes for early US baby boomers - using the data of the Health and Retirment Study (HRS), they find evidence that this group will work for a higher number of years. However, neither of these studies has its focus on the role of career

[6] See Herriot and Kasprzyk (1984).

[7] Detailed information can be found at the website of University of Michigan (`https://psidonline.isr.umich.edu/default.aspx`

interruptions and does not explicitly incorporate those in their models.

Using 27 waves of the German Socio-Economic Panel, Westermeier et al. (2012) take a closer look at the German baby boomers and their expected old-age provision. They use older birth cohorts to project employment histories of baby boomers by matching similar biographies. They find that baby boomers are expected to have on average lower pension entitlements than older cohorts. On a broader scope, Geyer and Steiner (2014) also use SOEP-data to examine effects of changes in employment patterns and pension legislation for different age groups. They employ a micro-simulation model to project employment and income biographies for future German retirees. They come to the conclusion that younger birth cohorts are more likely to face significantly reduced pension entitlements due to recent reforms and longer unemployment periods. Furthermore, the German Federal Ministry of Labor and Social Affairs regularly conducts the *Altersvorsorge in Deutschland* (AVID) report using specifically designed survey data to simulate expected future pension entitlements (for further information see, for example, Heinze (2010)).

Contrary to the models described above (Westermeier et al. (2012), Geyer and Steiner (2014)) and the one used in this chapter to simulate individual biographies, further approaches to quantify changes in politics or society with a life-cycle perspective are available. These are often based on structural models examining the optimal decision of individuals and households. Haan and Prowse (2014), for example, use the data of the German Socio-Economic Panel in order to develop a dynamic structural life-cycle model in which decisions with respect to employment, retirement, and consumption are illustrated. They quantify the fiscal effects of an increase in life expectancy on the pension system when, at the same time, the retirement age increases or the pension level decreases. The same authors (see Haan and Prowse (2015)) build a structural life-cycle model of savings and labor supply decisions in order to determine the optimal design of social insurance and assistance programs when the availability of a social insurance depends on labor supply decisions made in the context of the household. The find that a policy mix that mainly focuses social assistance that guaranteeing a permanent universal minimum household income is optimal. Closely related to this chapter (and even more recent than the first version of this chapter) is the work of Adda et al. (2017). They develop and use a dynamic life-cycle model of labor supply, fertility and savings that even takes occupational choices into account. Their work is based on German social security records (IABS data), survey data from the German Socio-Economic Panel (SOEP), as well as the Income- and Expenditure Survey (EVS). They estimate the life-time costs of children occurring due to loss of skills during interruption periods, lost earnings opportunities, and selection into more child-friendly occupations.

There are, to the best of my knowledge, no studies that use micro-simulation to quantify life cycle effects of career interruptions that are able to predict individual biographies. Potrafke (2007) conducts - using German Pension Insurance data - an empirical examination with some similarities to this research: He discusses how the timing of career interruptions affects pension entitlements by looking back at West Germans retirees of 2004. His estimations show that unemployment spells of men are more important in the middle part of an employment history while women's incomes do not exhibit significant effects of unemployment. However, parental leave in early parts of an employment history showed significant negative effects for women. But by looking at recent retirees, it is not possible to draw conclusions for people that are still working as ongoing trends, for example with respect to labor force participation (especially for women) and education, can be observed. Additionally, this approach is not feasible to quantify scenarios for different lengths of interruptions as it does not allow for the inclusion of counter-factual scenarios. Therefore, a simulation based prediction for future retirees can give further insight in the cost of career interruptions.

3.3 Model setup, data, and baseline results

The simulation model quantifies the effects of career interruptions on lifetime income. A career interruption does not only have negative effects in the short but also in the long run. This is due to the fact that interruptions will have negative consequences with regard to future income and the probability of re-entering the labor market due to the long-term loss of human capital. (Boll (2011a), for example, shows that substantial negative wage effects occur after re-starting an full-time employment as result of the earlier interruption.[8]) This chapter provides methods to quantify these effects and to distinguish their sizes between groups, especially men and women, and in time.

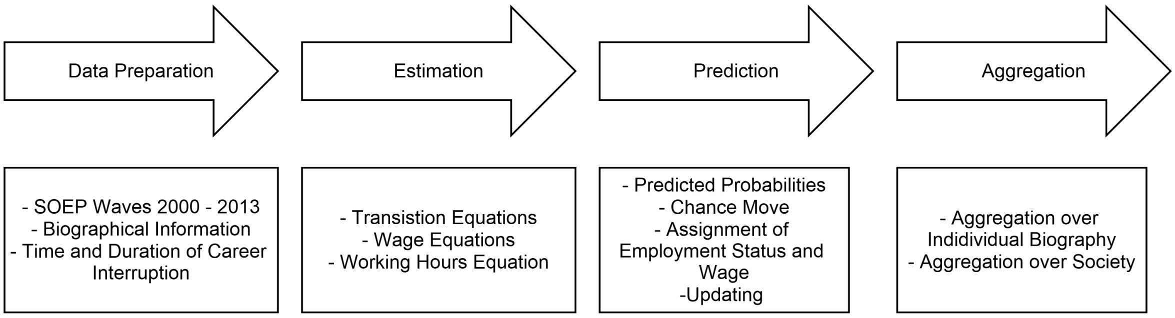
In principle, many methods are possible to model the development of employment biographies and to quantify the cost of career interruptions - those range from structural models that explicitly take preferences into account (see Adda et al. (2017)) over matching approaches (see Westermeier et al. (2012)) to the estimation of entire remaining biographies (see Geyer and Steiner (2014)). The model used in this chapter is driven by empirical estimates and does not rely on an assumed optimization behavior other than that implicit in the observed transitions in and out of employment. The model is also not as complex in its design in depicting choices compared to some structural models (see Haan and Prowse (2014)). The main advantage of this method is, however, that does not have to

[8]Contrary to Boll (2011a), this chapter does not condense the population into groups but predicts biographies for each individual in the sample. A further difference lies in the fact that this model projects biographies until retirement thereby capturing the consequences of interruptions for completed careers.

rely on additional assumptions and allows for an extrapolation of observed behavior to the future. Furthermore, subgroups can be studied easily as the model depicts the formation of employment biographies for each sample member. It also allows for the quantification of scenarios in a very intuitive manner. Thereby, the models answers the question how employment biographies would evolve, if today's observed relationships between individual characteristics and employment will continue to hold in the future. The model is, however, not designed as a general equilibrium model and effects of labor demand are not included. Throughout this chapter, it is assumed that additional labor supply will find the respective demand at predicted prices. Based on the individual characteristics of the previous period, biographies are updated for the following one. This updating process is carried out sequentially: in the first step, the extensive margin is determined, while, in the second step, intensive margin and wage are projected. Consequently, up to this point, the formation process of the wages and the decision whether or not an employment is assigned are not jointly determined. Nevertheless, information on (potential) wages is implicitly covered within the modeling framework: the decision whether or not to work crucially depends on factors like employment experience and education which also substantially determine wages (see Mincer and Ofek (1982) or Willis (1986)). Furthermore, up to this point, the model does not distinguish between different forms of employment like mini-job, full- or part-time employment - this distinction will be introduced in Chapter 4.

In particular, the simulation process used in this chapter consists of four steps: data preparation, regression, prediction, and evaluation: In the first step, the necessary information on the length of employment spells, the duration of the last career interruption, as well as the time since this interruption are calculated. The approach applies, in the second step, binary panel data regression methods to estimate the transitions between periods of employment and periods out of employment, using this biography data and further socio-economic characteristics. Furthermore, the determinants of working hours and hourly wages are estimated. These regression results are, in a next step, used to update the employment path until retirement - the predicted probabilities for beginning or ending an employment are calculated for every individual in the sample. An employment status is assigned to every sample member for the following period, based on the outcome of a random experiment. Additionally, each individual receives a predicted wage and predicted working hours for this period (and therefore the total yearly gross income) depending on the personal and household characteristics and the estimated regression coefficients. This updating process of employment status, working hours, and wage is iteratively repeated until each individual has reached the assumed fixed retirement age of 65. This provides a completed predicted biography for all sample members until the year 2037. Figure 3.1 provides a schematic description of the overall model structure.

Figure 3.1
Schematic description of the overall model structure



Source: Own illustration

In the fourth and last step, the analysis evaluates the cost of a career interruption in a counterfactual scenario by altering the length of a past interruption by one year for each concerned individual and the biography updating (step three) is repeated without altering the regression results of step two. Changing the starting conditions influences the entire prediction and by comparing the projected biographies in baseline and alternative scenario, the average life-time cost of an employment break can be calculated. In the next sections, the methodology is explained in greater detail:

3.3.1 Data and descriptive results

The model uses the data of the German Socio-Economic Panel (SOEP). The SOEP[9] is a representative survey of private households in Germany conducted since the year 1984 with about 30,000 respondents in roughly 11,000 households in 2012. It provides information on a wide range of topics like employment biographies, earnings, and socio-economic characteristics of the household members.[10]

The sample is restricted to persons over 40 and younger than 65 who have been employed for at least one year. This restriction is made for two reasons: Firstly, it is not within the scope of this paper to estimate the start of career interruptions due to childbirth, which can, at least to a large degree, be avoided by setting an age limit.[11] Secondly, it is intended to predict biographies until retirement while keeping the prediction horizon within a relatively short time frame. For estimation, the SOEP waves from 2003 to 2012 are used as these provide a reasonably large sample size as well as recent data. The SOEP-members of the 2012-wave (in the specified age group) form the basis for all predictions: their aging is simulated and their employment biographies are predicted until retirement.

[9]The waves SOEPv20 - SOEPv29 are used for estimation, prediction, and robustness-checks throughout the following analyses.
[10]For an overview see, for example, Wagner et al. (2007).
[11]Persons with an ongoing interruption due to a childbirth before their 40th birthday are included in the sample.

Chapter 3 uses the biographical data on the SOEP-respondents as the major source of information on employment histories. The SOEP's activity biographies provide yearly retrospective information on every respondent from the age of 15 up to the current age. This spell-data is aggregated in four states: 'employment', 'no employment', 'education', and 'retirement'. Furthermore, years with overlapping spells are ranked in a manner following Westermeier et al. (2012). Specifically, we assume that education and retirement are a person's dominating main activities when one or more further states exist in parallel - additional periods of employment and unemployment are therefore not considered in this case. This data is used to calculate the duration of past employment breaks, the duration of the current employment break for unemployed respondents, as well as the time elapsed since the last interruption (for employed respondents). At this point, no differentiation is made between types of interruptions (for example unemployment and childcare) as it is intended to construct a basic model that can serve as the basis for further extensions. This means that the effect of an average interruption is discussed as this study focuses on the average long-term cost of interruption and not on that of a specific interruption type. In addition to the biography data, SOEP data on socio-economic characteristics, most importantly on income, working hours, working experience, and education is used. Additionally, the model does distinguish between residences in East and West Germany.

Table 3.1 provides an overview of the relevant dependent and independent variables for the considered age group: The average sample member is, as of 2012, about 50 years old and works, if employed, about 34 hours a week. This average individual has accumulated about 20 years of full-time experience since first being employed and has interrupted an employment for three years. About 80 percent of the sample members are employed. The differences between the sexes are immediately apparent - women earn significantly less, work fewer hours, and are less likely to be employed. As expected, the employment biographies of those employed in 2012 and those not employed also vary considerably.

Career interruptions and their timing are in the focus of this study and will therefore be discussed in greater detail: Table 3.1 suggests that the average woman's interruption lasts more than three times longer than that of the average man. Men interrupted their employment for less than 1.5 years while this number approaches five years for women with an interruption. Figure 3.2 provides information on the distribution of the length of the last career interruption. It is apparent that the share of men with no interruption at all - about 50 percent - is substantially larger compared to that of women (about 20 percent). Long interruption periods are also a lot more common for women as men rarely interrupt an employment for more than three years. Therefore, women have to suffer substantial life-time and

Table 3.1
Descriptive results (SOEP, 2012)

	(Sex)		(Employment status)		
	Men	Women	Not employed	Employed	Total
Employment (%)	84.9	75.9	0	100	80.3
	(35.8)	(42.7)	(0)	(0)	(39.4)
Working hours	39.09	29.53	.	34.34	34.34
	(4.694)	(10.67)	(.)	(9.516)	(9.516)
Hourly gross wage	20.62	15.89	.	18.27	18.27
	(10.53)	(9.150)	(.)	(10.15)	(10.15)
Duration last interruption	1.414	4.665	7.275	2.040	3.070
	(2.992)	(6.582)	(8.220)	(3.779)	(5.394)
Time since interruption	10.04	11.20	.	10.85	10.85
	(9.393)	(9.315)	(.)	(9.363)	(9.363)
Number of children	1.430	1.662	1.656	1.522	1.548
	(1.160)	(1.129)	(1.271)	(1.117)	(1.150)
Age	50.49	50.42	51.18	50.28	50.45
	(6.484)	(6.389)	(6.925)	(6.298)	(6.436)
Full-time exp.	25.77	15.09	15.61	21.48	20.33
	(8.622)	(10.63)	(10.57)	(10.88)	(11.07)
Part-time exp.	0.831	7.135	3.769	4.110	4.043
	(2.565)	(7.995)	(6.166)	(6.899)	(6.762)
Observations					8220

mean coefficients; sd in parentheses

Source: SOEPv29, own calculations

old-age income losses.

The average career interruption dates back approximately the same amount of time for men and women (10 vs. 11 years). From Figure 3.3 however, it can be seen that the distribution of the interruption timing exhibits dissimilar patterns. Men's interruptions frequently date back only a short period of time while this distribution is more even for women. This indicates that men's biographies - if they interrupt at all - tend to be more volatile but that their interruptions also tend to be shorter than those of women.

3.3.2 Estimation results

The results of three groups of regressions drive the model and determine the forecast of the employment biographies for each individual. These regressions control the transition between spells of employment and phases without economic activity, the working hours, and the relative deviation from the average hourly wage and therefore all gross wages until retirement. Independent regressions determine employment status, working hours, and wages. This approach allows different explanatory factors to influence these three processes. All regressions are carried out separately for men and women.

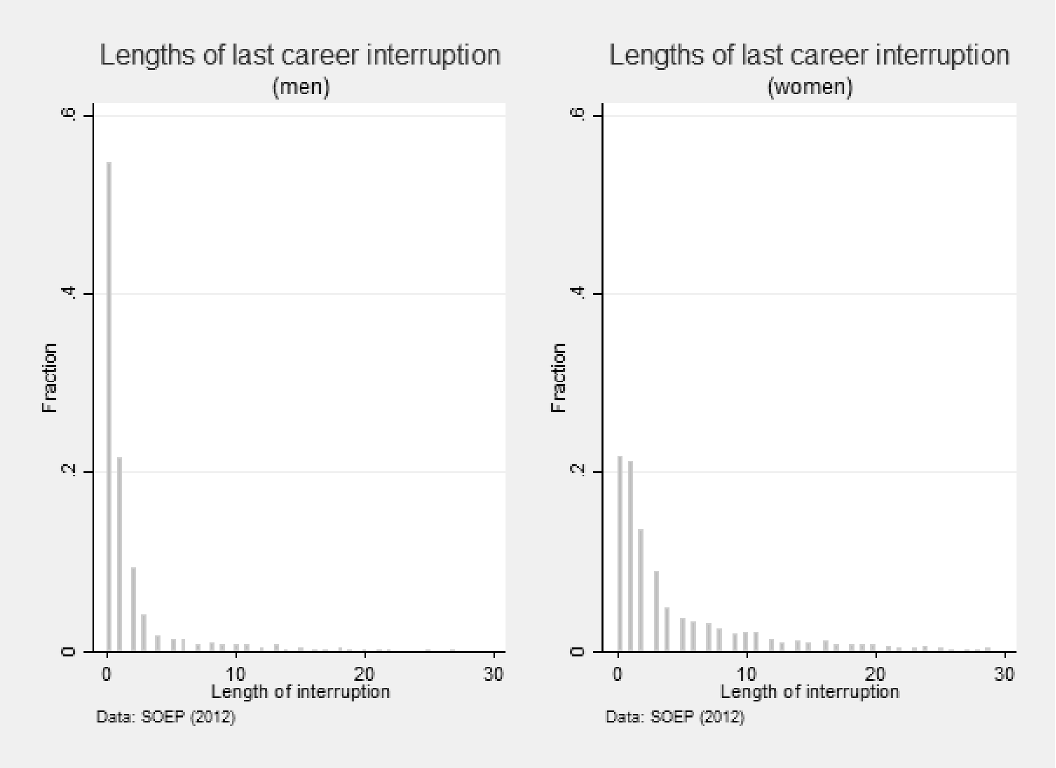
The independent variables are included as first lags in all regressions. This is done for two reasons: Firstly, this corresponds to the dynamic structure of the model where the employment of period t is determined by the characteristics of period $t-1$. Secondly, this is done to avoid endogeneity problems in the regression framework (see Wooldridge (2010)). The unbiasedness of the estimators is of lesser concern in the baseline scenario as the focus is purely on prediction. The counter-factual scenarios, however, require to address potential endogeneity issues as the effects of a change in a specific variable (length of interruption) are investigated. The inclusion of lagged independent variables avoids reverse causality problems as, for example, future wages have no causal effect on the employment experience of the past. Other relevant variables - like age - are, by definition, exogenous.

The sole distinction between men and women in the regression equations does, however, not exclude other important characteristics that are crucial for transitions, hours, and wages: For example, employment rates are lower for persons with a migration background.[12] Similarly, employment chances in Germany's eastern and western parts are still not alike and the likelihood of working is strongly depending on the number of children.[13] All these effects are included as independent variables in the

[12]See Statistisches Bundesamt (2016a).

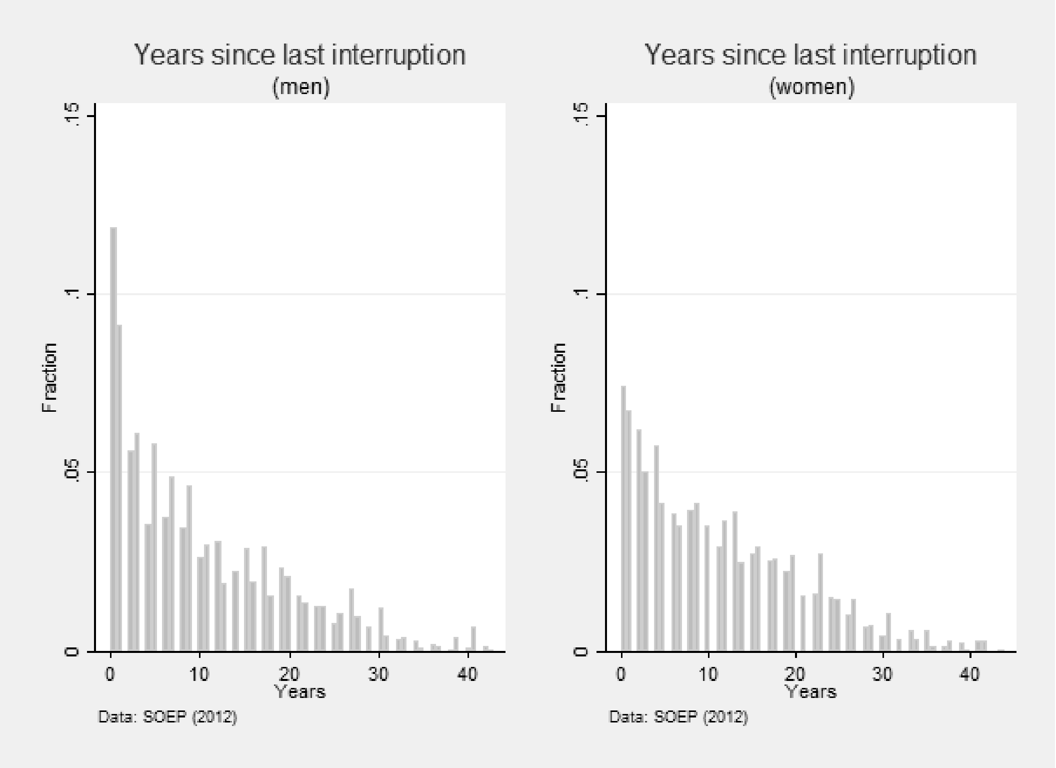
[13]See, for example, Drobnič et al. (1999) or Kreyenfeld (2009) for details.

FIGURE 3.2
Duration of career interruptions



Source: SOEPv29, own calculations

FIGURE 3.3
Years since last interruptions



Source: SOEPv29, own calculations

regressions but not in additional separate regressions. This is equivalent to the assumption that given those characteristics, the effects of the other independent variables remain unchanged - i.e. that there are no interactions.[14] Certainly, this assumption can be relaxed but this study only uses separate equations for men and women, because the projection of employment biographies is discussed in the context of gender questions, particularly with respect to employment interruptions of women.[15]

A similar situation arises in the discussion of the career interruptions - child or elderly care or unemployment do certainly exhibit different interruption patterns and also have different consequences. The model does not explicitly distinguish between these types, though the transition equations capture the causes for entering or leaving the various types of non-employment. Therefore, the non-employment periods within the model are of an average type. This is, however, not of concern within this study as the analysis focuses on the accumulated average interruption length, i.e. on the overall effect of an average interruption, even though this distinction is surely of concern for the affected individual. Generally, such an extended state space could still be implemented in the model, but would have major model revisions as a consequence. A binary transition specification would be no more feasible in this case. Furthermore, the number of transitions that have to be estimated increases quadratically with the inclusion of new career interruption types.

The following sections discuss the setup of the three regression groups and their results in greater detail.

Employment

Past career interruptions (as well as other factors) influence the beginning and the ending of an employment. Separate panel probit regressions (see, for example, Baltagi (2008)) for those currently working and those who are currently not employed determine the causes for these transitions. Here, emp_t equals one if a person is employed in period t while $nemp_t$ equaling one indicates that a person has left an employment.

$$emp_t^{\star,i} = c + \beta X_{t-1}^i + \mu_t + \nu_i + \epsilon_t^i \text{ if } emp_{t-1}^i = 1 \tag{3.1}$$

[14]The migration status was included in different specifications in robustness checks - independently of the specification, the results remained unchanged.

[15]This assumption is, nevertheless, relaxed in Chapter 4.

$$emp_t^i = \begin{cases} 1 & emp_t^{\star,i} > 0 \\ 0 & emp_t^{\star,i} \leq 0 \end{cases}$$

and

$$nemp_t^{\star,i} = c + \beta X_{t-1}^i + \mu_t + \nu_i + \epsilon_t^i \text{ if } nemp_{t-1}^i = 1 \tag{3.2}$$

$$nemp_t^i = \begin{cases} 1 & nemp_t^{\star,i} > 0 \\ 0 & nemp_t^{\star,i} \leq 0 \end{cases}$$

The explanatory variables are denoted as X. μ describes the time fixed effects and ν the individual heterogeneity which is assumed to be uncorrelated with the explanatory variables. ϵ is a $\mathcal{N}(0,1)$ distributed error term.

Table B.1 and Table B.2 in Appendix B show that a longer time since the last career interruption will, for both men and women, heavily reduce the risk to end an employment. As expected, greater employment experience reduces the risk of becoming unemployed. Experience effects are more pronounced for men, while the effect of children in the household is only of significance for women. Higher education creates better perspectives on the employment market for both sexes.

The determinants influencing those not working to reenter are similar to the effects describing the opposite direction (see Table B.3 and Table B.4). These results indicate that career interruptions will negatively affect employment in the long run - either through the direct negative effects of the interruption but also indirectly because of a reduced experience.

Working hours

The determinants of the number of weekly working hours h (for those being employed) are estimated in a linear random effects panel data model:[16,17]

$$h_t^i = c + \beta X_{t-1}^i + \mu_t + \nu_i + \epsilon_t^i \tag{3.3}$$

Again, all explanatory variables are included as first lags.

The regression results are presented in Tables B.5 and B.6 in Appendix B. Both, the time since the last interruption as well as its duration strongly influence the number of working hours (though

[16] That is, it is assumed that the individual heterogeneity is uncorrelated with the explanatory variables.

[17] In this analysis, the actual working hours are considered, as unlike the contractually agreed hours, overtime and overtime allowances determine the overall monthly gross wage which is relevant for the overall life-time income.

with a diminishing rate). The negative effect of interruptions on working hours is particularly strong for women. The same holds true for the presence of young children which is also a major influence on whether a career is interrupted for a longer period in the first place. Part-time experience, on the other hand, only has a negative effect for men. Consequently, interruptions have long-lasting effects on working hours, wages, lifetime earnings, and finally old-age income.

Wages

Hourly wage rates hw are determined in a two-step procedure.[18] At first, the change in the average hourly wage rate is estimated in a first-order auto-regressive model (see Hamilton (1994)) for both men and women. While women's wages are substantially lower as of 2012, this study estimates a faster wage increase for women. In spite of this faster increase, the change rate differences are not large enough to lead to equal hourly wages by 2035. In the second step, the relative deviation of the hourly wage rate dev_{hw} from the average hourly wage $\bar{hw}$ is regressed on explanatory variables in a random effects linear panel data framework. This two-step procedure follows the approach of Geyer and Steiner (2014). Table B.7 and Table B.8 in Appendix B show the results of the second-stage regression. As expected, wages are mainly driven by education and employment experience. But also career interruptions on their own are of substantial importance. Consequently, it is, already at this stage, apparent that career interruptions (and their timing) will negatively influence hourly wages also in the long run.

3.3.3 Updating process and prediction

Using an iterative process, this approach updates employment status, working hours, and wages for each individual in the sample based on the individual characteristics on the regression results described in Section 3.3.2. Here, it is assumed that the estimated effect sizes, respectively the regression coefficients, are constant throughout the prediction period.

At first, propensities for employment and non-employment are calculated using the explanatory variables of period $t-1$ and the estimated regression coefficients. Then, the realization of random variable, distributed uniformly on $[0,1]$ determines the employment status in the current period t.[19] If the model, for example, predicts, for certain levels of the explanatory variables, an 80 percent probability of staying employed but the realization of the random variable is 0.9, this individual will, in this model setup, end the employment. But if the procedure leads to an employment in

[18]In this analysis, overtime allowances are included as those can be a significant part of the total life-time income.

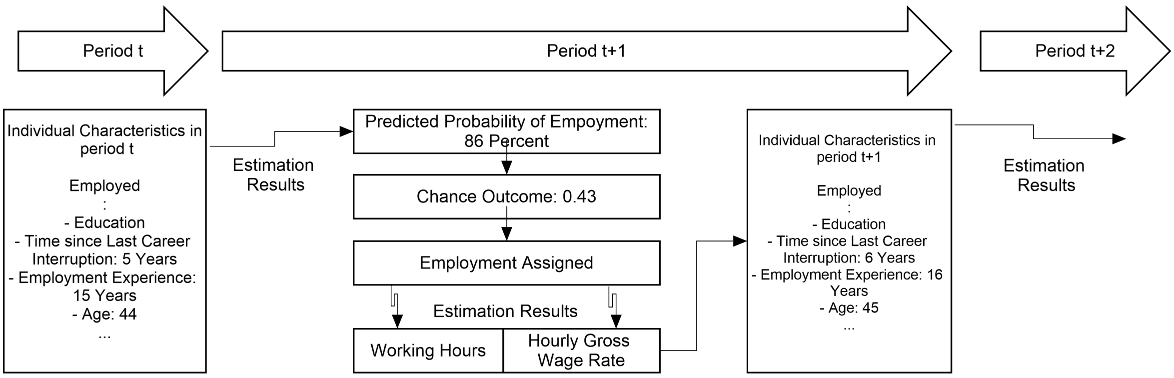
[19]To achieve a consistent prediction in the baseline and the counter-factual scenario, the same random draws are used in both.

period t, working hours in t are updated using the characteristics of period $t-1$ and the estimated regression coefficients. The analysis assumes that a predicted employment of less than 35 hours per week constitutes a part-time work. The development of the average wage rate change is estimated separately for men and women in an auto-regressive model and the resulting change rates are assumed to be constant throughout the prediction period. Deviations from this average wage rate are predicted for every period based on the explanatory variables of the previous period. This procedure leads to a monthly gross wage gw of

$$gw_i^t = emp_i^t * h_i^t * \bar{hw}_t * (1 + dev_{hw,i}^t) * 4.34 \tag{3.4}$$

with an average month having 4.34 weeks. After determining the employment characteristics, all relevant explanatory variables are updated based on the predicted outcomes in period t (time since interruption, duration of interruption, employment experience, as well as age and the number of young children). Based on the updated explanatory variables and the regression results, this procedure is repeated until retirement is reached. Furthermore, a fixed retirement age of 65 for the entire population is assumed, as the timing of a retirement is not in the focus of this study.

FIGURE 3.4
Schematic description of the updating process for one exemplary individual



Source: Own illustration

Figure 3.4 provides an example of the updating process for just one period and one specific individual with a given set of characteristics. It is, for example, assumed that this person is employed in period t , 44 years old, and has fifteen years employment experience. Based on these and further characteristics as well as on the estimation results, the predicted probability of being employed in the following period $t+1$ can be calculated. We assume that this probability is 86 percent. If a random number of, for example, 0.43[20] is received, an employment is assigned for period $t+1$. Based on the

[20]Meaning a random number that is smaller than 0.86.

estimation results and the individual characteristics, working hours and wage can be attributed to this person. This information is used to update the personal characteristics - this individual now possesses an additional year of employment experience (and has also aged by one year). These updated attributes are the basis for the prediction process for period $t+2$.

This model does, however, not calculate the exact effects of the employment biographies on the amount of pension, as this would, due to the complexity of the German pension scheme (see, for example, Börsch-Supan and Wilke (2004)), require additional assumptions as well as the prediction of the biographies of all current and future employees.[21] As, however, in the German pension system, lifetime income and pension are closely related, the accumulated gross wages serve as a good proxy for old-age income.

3.3.4 Results from baseline scenario

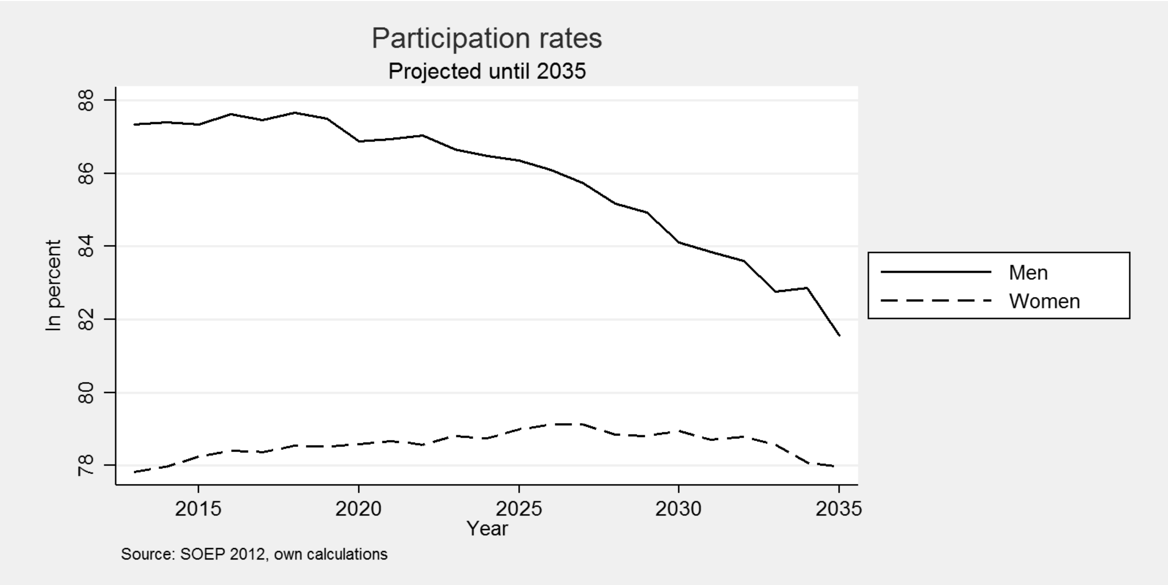
The baseline scenario constitutes the foundation for all further analysis and serves as a benchmark for the counter-factual scenarios. To reduce the element of chance of a single projection, the prediction process is repeated 100 times and the results are averaged. Additionally, these repetitions allow to assess the uncertainty in the prediction process. Robustness checks also show that the results described below are not sensitive with respect to the specific time frame of the estimation sample. Using, for example, only data from 2008 to 2012 for estimation does not significantly change the outcomes.

This method allows a yearly evaluation of all relevant variables in the prediction process. Figure 3.5, for example, depicts the projected employment rates for the sample members under 65 up to the year 2035 in the baseline scenario. It can be seen that men's employment rates drop from about 87 to about 82 percent in 2035. This is mainly due to the fact that the population is aging and that older cohorts tend to have lower employment rates than younger ones. This effect is not visible for women: their employment rates remain approximately constant. This indicates a further increase in women's participation rates in the coming years as, at the moment, these rates are lower at higher ages while this is no more the case in this baseline projection.

Taking the mean over all projected employment biographies, it turns out that the average sample member will be employed for about another 12 years and will be out of employment for approximately 2.5 years. But differences between the sexes are standing out - women are predicted to spend 50 percent more time out of an employment than men (see Table 3.2). Substantial differences can also be

[21] See Chapter 4 for the correspondingly extended model.

Figure 3.5
Projected employment rates for men and women



Source: SOEPv29, own calculations

found in the number of working hours. The average woman works about 10 hours less compared to men. These results and lower wage rates of women immediately translate to a substantial differential in gross life-time income which is in line with recent literature on the gender pension gap in Germany (see, for example, Hänisch and Klos (2014)) and the prediction that it will not quickly close in the future.

Table 3.2
Predicted average outcomes for all sample members in baseline scenario

Sex:	Interruption (years)	Employment (years)	Working hours	Lifetime income
Men	1.92	12.41	37.69	659,415
	(0.014)	(0.014)	(0.005)	(760)
Women	3.07	11.25	26.25	320,758
	(0.019)	(0.019)	(0.011)	(601)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

3.4 Scenarios: Results

The long-term cost of career interruptions is quantified in two scenarios. In each of these scenarios, it is established how the entire future employment biography - employment status, working hours, and wages - of each sample member reacts to an assumed change in the completed part of the career path, that is to a reduced length of a past interruption period. In particular, this research is not interested in the additional income during the assumed extra employment year and it does not assume that, due to some unlikely policy, all employment breaks will stop immediately. This study is merely interested in the effects of an improved starting position for the future employment path due to a shorter interruption. It focuses on the complete future life-cycle income gain as a result of such a shortened break. Equivalently, this scenario quantifies the cost of a year of interruption when this additional employment is not assumed to no more exist. Therefore, the cost of one year of interruption is quantified by comparing the average lifetime incomes of the projected employment biographies with and without the reduced interruption length. As this procedure is carried out for each individual in the sample, aggregation and weighting will provide the approximate aggregate cost of non-employment - the aggregate incomes in baseline and alternative scenario can be compared. To capture all relevant aspects and to cover the most important affected groups, the following scenarios will be discussed:

- Scenario 1: Current employment break starts one year later
- Scenario 2: Just completed career interruption ends one year earlier

These scenarios are selected in a way to discuss two particular situations: that of a person who is still interrupting a career and that of a person who has just reentered employment. One might expect that a person, whose career is interrupted, might benefit from a shorter interruption due to better reentry conditions leading to a completely different employment path. On the other hand, one can assume that more time of being continuously employed will lower the risk of future unemployment. Without any doubt, different scenarios, like a shortened interruption length for every person with an interruption, could be considered. The two chosen scenarios have, however, the advantage that they reflect the interruption's consequences very pronounced and most directly, since both scenarios focus on the effect of a one year change in the interruption length while longer durations are not regarded. Certainly, the interruption cost does not need to be linear in their length but the one year effect still provides a good first approximation for the cost of longer interruptions. Furthermore, many people will not be able to substantially decrease their interruption time (for example due to the presence of young children), but a one year reduction will often be feasible.

The estimators for the average length of the interruption (in years), the average number of employment years, the average working hours, and the average lifetime income are presented for baseline and alternative scenarios. Standard errors of these estimators are given in parentheses below the estimator. In all cases, the difference in lifetime income between baseline and alternative scenario is significant, though varying in size.

3.4.1 Scenario 1 - Shorter ongoing interruption

Different groups are affected by a shorter interruption to a varying extent: Those who are currently not working might find it easier, due to the reduced interruption length and the implied smaller loss of human capital, to re-start an employment and to discover a way back to an uninterrupted biography, resulting in an increased lifetime income and increaed security at an old age. Due to the close link between lifetime income and pension, this scenario is directly related to the ongoing discussion on poverty among the elderly and its avoidance as this group is particularly at risk of suffering from inadequate income at an older age.

To quantify the lifetime effects of an assumed shortened interruption, this scenario counter-factually supposes that those who are, as of 2012, interrupting an employment for more than one year, did, in fact, continue their last employment for an additional year - i.e. that their current interruptions are one year shorter. It is immediately apparent that this group is especially vulnerable to old-age poverty when comparing their baseline average projected income with that of the population as a whole: they are not only expected to work less hours in employment phases, but the projection also suggests that the average duration of future unemployment periods is substantially longer. Not surprisingly, this group is only able to obtain a fraction of the income of the entire population until retirement (see Table 3.3).

Table 3.3
Predicted average outcomes for affected sample members in scenario 1 - baseline

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	8.04	3.79	33.66	132,112
	(0.154)	(0.154)	(0.072)	(1876)
Women	8.74	4.42	20.16	85,651
	(0.096)	(0.096)	(0.084)	(977)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

The simulations suggest that the effect of an additional employment year in the past biography is substantial - the improved starting position leads to almost one additional employment year in the future and is on average worth about 30,000 Euros for men and 25,000 Euros for women. Though these effect sizes do not differ heavily between men and women in absolute numbers, the relative improvements for women are clearly more pronounced as they are accumulating less income than men. As women are more prone to career interruptions, this amount of money should not be underestimated with regard to its effects on old-age poverty and on closing the gender pension gap (see Table 3.5).

This number is particularly remarkable considering the fact that the assumed extra employment year in the past is not part of this calculation.

Not surprisingly, the youngest cohort (aged from 40 to 45 as of 2012) accumulates the largest profit from a shortened interruption, though the gain of the second youngest group is, for a shorter period of time, only slightly lower. Equivalently, this leads to the conclusion that employment breaks between the ages of 45 and 50 - a period with rather high wages - are particularly costly (see Table 3.4). It is well known that career interruptions continue to have an effect over long time periods, but that this effect is a diminishing one. The simulations acknowledge that this effect is, in fact, diminishing for the average affected individual, but they also suggest that this diminishing is proceeding with a fairly slow rate (see Table 3.4). For example, the effects of the interruption only tend to drop substantially shortly before retirement. The simulation shows that about 40 percent of the gain of an additional employment year is realized in the second half of the remaining employment biography. In turn, this fact reveals how severe the long-term effects of career interruptions really are.

The effect of the shortened employment break on the aggregate, society-wide[22], income is relatively small (see Table 3.6) - the increase amounts to about 1 percent. Keeping in mind that only a relatively small part of the population is affected by the hypothesized change and that no immediate reentry is assumed, these social effects should still be considered. For the affected group and the average individual, the cost of career interruptions are in any case substantial and persistent.

3.4.2 Scenario 2 - Recent reentry

Not only those currently interrupting their career as in scenario 1, but also persons having already restarted an employment should benefit from a more continuous employment biography by having more experience and less time out of employment leading to higher wages and a safer job. Therefore, the second scenario assumes that those who have newly begun an employment in 2012 did in fact restart their careers one year earlier. Interruptions of less than one year are excluded from the analysis as these cases are likely to be related to transition phases between different jobs or short periods of search unemployment which are likely to have different effects compared to all other causes of not working. One can safely assume that such a short and often unavoidable interruption will, unlike any other interruption, have no or very little long run effects.

This group differs substantially from the one discussed in scenario 1: Scenario 2 regards recent

[22]Within the discussed age group.

Table 3.4
Predicted changes to baseline results in scenario 1 for affected group by age-group and year

Year	Cumulated income difference					Difference in weekly working hours				
	Age (in 2012)									
	40-44	45-49	50-54	55-59	60 and older	40-44	45-49	50-54	55-59	60 and older
2013	2493	3715	2494	2640	1668	3.22	4.66	2.89	3.23	2.15
2014	4609	6453	4634	4754	3100	2.65	3.51	2.48	2.64	1.87
2015	6607	8867	6655	6722	4354	2.39	3	2.24	2.41	1.56
2016	8382	11058	8504	8567	5043	2.03	2.61	2.01	2.22	0.82
2017	10091	13279	10263	10379	5522	1.88	2.52	1.84	2.14	0.56
2018	11782	15383	12052	12127	5522	1.79	2.31	1.82	2	0
2019	13460	17397	13827	13493	5522	1.72	2.19	1.75	1.47	0
2020	15201	19358	15518	14546	5522	1.73	2.1	1.63	1.1	0
2021	16850	21322	17187	15369	5522	1.6	2.06	1.56	0.83	0
2022	18567	23186	18732	15861	5522	1.61	1.93	1.43	0.41	0
2023	20232	25027	20272	15861	5522	1.5	1.85	1.41	0	0
2024	21951	26770	21637	15861	5522	1.52	1.72	1.19	0	0
2025	23739	28438	22728	15861	5522	1.55	1.62	0.87	0	0
2026	25383	30153	23525	15861	5522	1.42	1.63	0.65	0	0
2027	27078	31768	23628	15861	5522	1.42	1.52	0.1	0	0
2028	28675	33393	23628	15861	5522	1.31	1.52	0	0	0
2029	30254	34658	23628	15861	5522	1.25	1.2	0	0	0
2030	31767	35540	23628	15861	5522	1.18	0.84	0	0	0
2031	33302	36182	23628	15861	5522	1.19	0.57	0	0	0
2032	34813	36451	23628	15861	5522	1.15	0.21	0	0	0
2033	36263	36451	23628	15861	5522	1.09	0	0	0	0
2034	37396	36451	23628	15861	5522	0.83	0	0	0	0
2035	38283	36451	23628	15861	5522	0.65	0	0	0	0

Source: SOEPv29, own calculations

Table 3.5
Predicted average outcomes for affected sample members in scenario 1 - alternative

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	7.18	4.66	34.43	163,363
	(0.135)	(0.135)	(0.070)	(1937)
Women	7.74	5.42	21.24	109,806
	(0.103)	(0.103)	(0.042)	(1130)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

Table 3.6
Predicted average outcomes for all sample members in scenario 1 - alternative

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	1.84	12.49	33.66	662,109
	(0.015)	(0.015)	(0.04)	(775)
Women	2.90	11.43	26.28	325,006
	(0.014)	(0.014)	(0.015)	(580)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

returners, while the affected persons of the first scenario may often have left the workforce for good - hence, it does not come as a surprise that this group is expected to collect more income and to accumulate a larger number of employment years (see Table 3.7). Compared to the entire population (see Table 3.2), this group, in particular men, is still worse off and more likely to be susceptible to poverty after retirement.

Table 3.7
Predicted average outcomes for affected sample members in scenario 2 - baseline

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	3.08	10.64	35.91	418,989
	(0.167)	(0.167)	(0.067)	(5933)
Women	3.12	13.56	21.33	299,983
	(0.105)	(0.106)	(0.076)	(2904)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

The simulation results show that a shorter interruption causes improvements which are similar to those of the affected group of scenario 1, though at a higher income level. Yet, the effect sizes are switched between the sexes - the average man gains about 25,000 Euro while this number increases to approximately 30,000 Euro for women. With this increase, the average reentering woman reaches the income level of the entire female population and closes the gap towards the male population by about 3 percentage points. This underlines that the long-term gains of early reentry should clearly not be underestimated. These life-time improvements originate to a large degree from increased wages due to a less interrupted career. The growing number of hours and employment years also has an influence, which is, however, considerably smaller than in the first scenario.

Going beyond the aggregate figures, the detailed examination by age-group shows interesting characteristics in the projected income improvements. In this scenario, the aggregated improvement of the youngest cohort is clearly the largest, both in absolute as well as in relative terms, while the relative differentials between the older groups are small (see Table 3.8). But most notably and contrary to the results of scenario 1, the positive effects of an additional employment year are not only slowly decreasing, the youngest cohort's income change does actually increase over a period of time. This stems from the fact that in particular this age-group is disproportionately highly expanding its working hours as an implication of a more continuous career path.

The effect of the changes in scenario 2 on the society's aggregated accumulated income is small (see Table 3.9) - this is essentially a consequence of the fact that the number of people starting an employment in a specific year after a break is small compared to the entire population. Still, one has to consider that the scenario is only a snapshot at one point in time and that many people will be restarting an employment at one point or another of an employment biography.

3.5 Conclusion

In combining micro-simulation with econometric methods, this chapter provides a tool to quantify the cost of employment breaks by projecting, comparing, and aggregating the outcomes of individual employment biographies using German micro data. The effects of a reduced duration of a career interruption on life-time income are evaluated in scenarios for different subgroups and the consequences of a variation in the interruption's occurrence in time are examined. Going beyond the implications for the average affected individual, the model is able to approximate the society-wide cost of longer interruptions - or, equivalently, the gains of shorter interruptions - by aggregating the individual changes.

A study by Potrafke (2007) is related to this work as he estimates the effect of a career interruption's timing on the pension incomes of the pensioners of 2004. The method used in this chapter is, however, the first to simulate individual employment biographies to quantify the cost of career interruptions and is thereby not only able to quantify varying scenarios but also able to calculate those for future retirees in a way that takes ongoing social developments into account. Boll (2011b) empirically predicts the wage patterns of women after a reentry. Specifically, she describes the wage

Table 3.8

Predicted changes to baseline results in scenario 2 for affected group by age-group and year

Year	Cumulated income difference					Difference in weekly working hours				
	Age (in 2012)									
	40-44	45-49	50-54	55-59	60 and older	40-44	45-49	50-54	55-59	60 and older
2013	1791	1491	1480	1076	1011	1.25	1.13	1.24	0.87	0.81
2014	3602	2882	2682	2532	1917	1.3	1.11	1.03	1.3	0.73
2015	5296	4316	4025	3796	2646	1.21	1.19	1.16	1.13	0.7
2016	7026	5776	5504	5027	3311	1.2	1.17	1.4	1.08	0.57
2017	8609	7255	6877	6349	4041	1.08	1.21	1.28	1.17	0.41
2018	10293	9034	8480	7925	4041	1.13	1.48	1.49	1.51	0
2019	11772	10728	9927	9155	4041	0.98	1.43	1.32	1.08	0
2020	13464	12115	11328	10293	4041	1.1	1.11	1.3	1.03	0
2021	15223	13453	12875	10640	4041	1.1	1.01	1.42	0.36	0
2022	16960	14876	14334	10738	4041	1.1	1.08	1.24	0.08	0
2023	18833	16331	15696	10738	4041	1.18	1.17	1.22	0	0
2024	20815	17734	16823	10738	4041	1.31	1.09	0.93	0	0
2025	22939	19094	17960	10738	4041	1.46	1.06	0.98	0	0
2026	25091	20444	18463	10738	4041	1.39	1.03	0.41	0	0
2027	27240	21824	18887	10738	4041	1.37	1.04	0.33	0	0
2028	29314	23348	18887	10738	4041	1.33	1.14	0	0	0
2029	31455	24846	18887	10738	4041	1.38	1.13	0	0	0
2030	33715	26112	18887	10738	4041	1.38	0.96	0	0	0
2031	35855	26929	18887	10738	4041	1.25	0.59	0	0	0
2032	37804	27645	18887	10738	4041	1.11	0.51	0	0	0
2033	39723	27645	18887	10738	4041	1.09	0	0	0	0
2034	41190	27645	18887	10738	4041	0.81	0	0	0	0
2035	42358	27645	18887	10738	4041	0.66	0	0	0	0

Source: SOEPv29, own calculations

Table 3.9
Predicted average outcomes for affected sample members in scenario 2 - alternative

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	2.74	10.98	36.19	441,950
	(0.157)	(0.157)	(0.068)	(5606)
Women	2.89	13.81	22.21	328,611
	(0.115)	(0.115)	(0.039)	(3706)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

Table 3.10
Predicted average outcomes for all sample members in scenario 2 - alternative

Sex:	Interruption (years)	Employment(years)	Working hours	Lifetime income
Men	1.91	12.42	37.70	659,831
	(0.014)	(0.014)	(0.05)	(781)
Women	3.07	11.26	26.27	321,450
	(0.018)	(0.017)	(0.011)	(587)

mean estimates; standard errors in parentheses
Source: SOEPv29, own calculations

loss in these phases for different stylized biographies. This study extends the work of Boll (2011b) by simulating the entire biography of each individual in the sample. As a result, the long lasting nature of career interruption cost for the average individual becomes apparent.

The projected future income increase as a consequence of a one year reduction of the interruption length are of a similar order of magnitude for those who recently reentered and those who are currently not employed. This improvement amounts to about 25,000 Euros for both groups, though the causes of this increase are not identical. As a result of the relative smallness of the affected group, aggregate society-wide income raises tend to be small. But despite of their size, these effects are still not negligible. While it is well known that employment breaks continue to have an effect long after the end of an interruption, this chapter shows how substantial the aftermath will be. The simulations suggest that as much as 40 percent of the effect of an interruption can occur in the second half of the period between reentry and retirement for the average affected individual. This indicates that the cost of an employment break effectively ceases only within a short period before the retirement of an average individual. But it does certainly not mean that an individual with a continuous employment biography after the interruption will suffer these losses, but interruptions reduce human capital and make further interruptions more likely resulting in the lasting negative effect for the average individual.

By not only providing qualitative but quantitative measures for the cost of career interruptions and the benefits of reentry, the presented methods deliver useful information in matters of the current discussion on old-age poverty in Germany and provide additional knowledge on the gender pension gap, the difference in average old-age incomes between men and women, and its potential future development.[23] As such, this model is a valuable instrument in the assessment of long-ranging effects of policies encouraging the restart of an employment, as it is able to quantify the long-run advantages of such a decision. It is apparent from these results that, for example, the extension of childcare in Germany for young children in recent years will also have a substantial positive influence on life-time income due to its positive influence on the employment of women (see Unterhofer et al. (2017)). Additionally, on the individual level, these results provide new information on the risks of employment interruptions when deciding whether or not to restart a career.

The model is not designed as a general equilibrium model - in particular, the labor demand side is not specified in this framework. Consequently, it is assumed throughout this analysis that labor supply will always find the corresponding demand. Certainly, various types of interruptions, like being unemployed or being out of the workforce, affect biographies in different ways. Beblo and Wolf (2002), for example, point out that interruptions caused by unemployment are especially harmful for men while women's income seems to be mainly influenced by parental leave periods or being out of the workforce. At this point, interruption types are not part of the model as it is intended to primarily provide a comprehensible and fundamental model that focuses on the cost of an average career interruption. In general, the model can be extended in various ways: For example, separate equations not only for men and women but also for people with and without migration background or children could be estimated. The same holds true for the distinction between East and West Germany. While these characteristics are included individually in all estimation equations, allowing for separate equations for all combinations of characteristics would enhance the flexibility of the model. Similarly, a differentiation between various types of employment, like full- and part-time work could be made. Many of these concepts are included in Chapter 4.

[23] See also Chapter 4.

Chapter 4

The Role of the Mini-job in the Long-Term Development of the Gender Pension Gap

4.1 Introduction

Gender differences in pensions have gained increased attention in recent years, given that they are even more substantial than the wage gap.[1] However, little is known on how Germany's gender pension gap - the relative difference between the average own (non-derived) pension income of men and women - can be expected to develop in the future. In the context of old-age income, particular attention is paid to a specific form of marginal employment - the mini-job - that is seen as especially harmful with respect to the economic stability in old age. Mini-jobs are problematic as low social security contributions provide an incentive to remain in this form of employment. Because of the low wages, only very limited pension rights can be obtained in this period. Given that among the middle-aged, predominantly women are working in mini-jobs and because mini-job and pension gap are therefore profoundly connected, naturally the question arises how large the effect of mini-jobs on the gender pension gap really is and whether regular part-time work would be a sensible way of significantly closing this gap.

It is the goal of this paper to gain knowledge on the long-term development of the German gender pension gap and on the impact of the mini-job with respect to its size. Particular focus is placed on the gap in the statutory pension scheme, by far the most important pillar of the German pension system. To achieve this goal, a complex micro-simulation model is developed. This model is able to predict employment biographies until retirement, their pension gap, as well as the gap development

[1]I would like to thank Carsten Schröder, C. Katharina Spieß, Sven Stöwhase, Katharina Wrohlich and seminar participants at Fraunhofer FIT for their comments and discussions.

for the current retirees. Additionally, this model allows for the quantification of scenarios. It is able to calculate the development of the gender pension gap for the hypothetical case in which a regular part-time employment is chosen instead of a mini-job. To the best of my knowledge, this model is the first to predict the development of the total pension gap and also the first to quantify the consequences of mini-jobs in scenarios. It thereby exceeds earlier approaches that either only calculated the pension gap at retirement (see Westermeier et al. (2017)) or use only specific cohorts in prediction (see Frommert and Strauß (2013)).

In the German pension system, the development of the gender pension gap is predetermined, with a relatively long notice. This model is able to quantify how long the gender gap will remain of importance and develop in the long run. It is able to shed light on the role of the mini-job in the formation of the gap and thereby able to show the maximum influence policies discouraging mini-job use can have in decreasing the gender pension gap. It also provides additional knowledge of the long-term capabilities of policies in changing the outcomes of the German pension system. Finally, this chapter provides evidence on the size of the society-wide negative effect of mini-jobs.

The results of the micro-simulation suggest that the gender pension gap will continue to decrease within the prediction horizon. Based on the simulation model and after statistical adjustment to the latest available data, it is estimated that the gender pension gap in the statutory pension scheme currently amounts to approximately 52 percent. For the current retirees, the gap will drop to about 47 percent at the end of the prediction period. This suggests that, as of today, the gender pension gap is already smaller for younger retirees. The pension gap of the today's employed cohorts at retirement is expected to decrease from about 47 percent to 33 percent. These results lead to a 15 percentage point decrease in the overall gap and a gap of approximately 37 percent percent in 2038. In a scenario where mini-jobs are replaced with regular part-time work, the gender pension is expected to decrease by about 1.3 percentage points. The building up process of the gap decrease is, however, very slow - this illustrates how limited the political opportunities in changing the gap within a reasonably short time frame are.

The rest of this chapter is structured as follows: First, a brief review of the relevant literature is given and the mini-job is introduced. Then, the model is introduced - special emphasis is laid on the innovation over the previous model as described in Chapter 3. In a next step, the results of the gender pension gap prediction are discussed. Afterward, the quantification of the mini-job scenario is presented. The final section provides a summary and conclusion.

4.2 Previous literature

While the gender differences in wages received at lot of attention (see, for example, Blau and Kahn (2016), Arulampalam et al. (2007), Plantenga and Remery (2006) or Wrohlich and Zucco (2017)), the gender pension gap, the difference in the average own pension income of men and women, has only been discussed more frequently in the last few years. An excellent overview on the situation in the European Union - primarily based on EU-SILC data - is given from Bettio et al. (2013). They provide conclusive evidence that a large gender pension gap is a particularly severe problem in Germany. This supports the importance of this topic. They show that Germany's gender pension gap is the second largest within the entire European Union, even though their EU-SILC based evaluation provides a slightly lower gap estimate than this analysis. Haan et al. (2017) support this hypothesis in a comparative study for Germany, Denmark, and France using data of the 'Survey of Health, Aging and Retirement in Europe' (SHARE).[2] In a descriptive study for the German Federal Ministry for Family Affairs, Flory (2011) uses the *Alterssicherung in Deutschland* (ASID) survey to provide evidence that the overall gender pension pension gap was as large as 60 percent in 2007. In the following years, various approaches were used to gain insight in the determinants of this gap. Especially decomposition analysis was often utilized (for technical details, see, for example, Jann (2008) or Fortin et al. (2011)). Both Frommert and Strauß (2013)[3] and Chapter 2 of this thesis suggest that employment experience and differences in education can explain a large part of the gender pension gap (going beyond the decomposition of the mean, Chapter 2 shows that the influence of these factors on the gap is not constant over the pension income distribution). Since the differences in employment and education have diminished (see Statistisches Bundesamt (2016b)), one could expect that the gap will continue to close in the future. Up to this point, however, no quantitative information on the expected development of the pension gap is available.

The mini-job, a specific German form of marginal employment (for details see also the next section), on other hand, received a lot of attention in politics as well as research. It this particularly the case since the reforms of this form of employment of the early 2000s. Details on the use of the mini-job and its development can be found in Minijobzentrale (2017).[4] An extensive descriptive survey on the socio-demographic characteristics of those mini-jobbers for whom a mini-job is the main source of earned income is provided from Körner et al. (2013). They use the data of the Federal

[2]For further information on the SHARE survey, see Börsch-Supan et al. (2013).

[3]Frommert and Strauß (2013) use the survey *Altersvorsorge in Deutschland* (AVID) to project employment biographies of two cohorts and use decomposition techniques to examine the gender old-age income differences.

[4]The *Minijob-Zentrale* is the official authority responsible for the administration of mini-jobs and has thereby access to all relevant information.

Employment Agency and conduct a survey specifically designed for this purpose. The number of men and women with mini-jobs in different age groups is of particular interest for this study (for details see also the next section). Studies observe an increase in precarious employment in the last decades (see, for example, Brady and Biegert (2017)). A substantial part of this precarious employment can be attributed to mini-jobs that have increased in importance for both men and women since the 1980s (Brady and Biegert (2017), page 10). The potential negative effects of mini-jobs have also been discussed extensively within both political and academic circles: Shortly after the mini-job reform of 2003, Steiner and Wrohlich (2005a) conclude in a study based on data of the German Socio-Economic Panel (SOEP[5]) that a small negative participation effect of the reform was offset by a negative hours effect and that this reform was thus unable to increase employment in the low-income sector. Using a behavioral micro-simulation model with the data of the German Socio-Economic Panel, Bargain et al. (2010) support the findings of Steiner and Wrohlich (2005a). Klenner and Schmidt (2011) stress that especially women, due to an involuntary chosen mini-job, will follow a path of continuous precarious employment. This also increases the risk of being poor after retirement. Galassi (2017) intensively discusses the various negative effects of mini-jobs - like a substitution of regular employment or a locking-in in the low-pay sector - but also examines the transitions to regular employment.[6] One phenomenon of the mini-job is particularly noticeable: an intense bunching at the mini-job threshold. A behavioral explanation is provided by Tazhitdinova (2017).

Dynamic behavioral micro-simulation is a powerful tool to assess both the effects of reforms in the pension system as well as that of policies like the mini-job. Introductions to micro-simulation techniques in the context of economic policy can, for example, be found in Merz (1994), O'Donoghue (2001) or Gupta and Kapur (2000). Micro-simulation techniques are also, though not frequently, used to to predict and examine the development of employment biographies in the context of employment and retirement. International examples can, for instance, be found in Lemieux (2006) or Michaud and Rohwedder (2008). In the context of German policy reforms, different approaches in the prediction of employment biographies are used: Using Socio-Economic Panel-data, Westermeier et al. (2012) match employment pattern from different cohorts to extend employment biographies until retirement, showing that the baby boomer generation expects less pension income than their elders. Geyer and Steiner (2014) use SOEP-data to predict the entire remaining employment biography in their micro-simulation model they use to analyze pension entitlements for different cohorts. Haan and Prowse (2014), on the other hand, develop a dynamic structural life-cycle model in which employment, retirement, and con-

[5]See Wagner et al. (2007).

[6]The study uses linked employer-employee data provided by German Institute for Employment Research.

sumption decisions are regarded.[7] Simulation models that forecast aspects of the gender pension gap are rare: Frommert and Strauß (2013) use data of the survey *Altersvorsorge in Deutschland* (AVID) to predict the gender pension gap for two age groups. Nevertheless, they neither offered an estimate for the entire gap nor explained their methodology in any further detail. Westermeier et al. (2017) provide the most recent - also SOEP-based - approach in using micro-simulation, using SOEP data to predict the gender pension gap at retirement - but results for the overall gap are not shown. To the best of my knowledge, no models that are able to capture the effects of the mini-job on the gender pension gap currently exist.

4.3 The mini-job

The mini-job is a German form of marginal employment where the wage is not allowed to exceed a specific amount. As of 2017, this amount reached 450 euros per month. The mini-job is subject to specific tax and social security regulations. Taxes and social security contributions are, to a large degree, offset as a lump sum transfer by the employer. The employee is only liable to pension scheme contributions but can be exempted upon request. The exact amount of social security contributions can vary between different types of mini-jobs (for example, mini-jobs in households or the commercial sector).

The concept of the mini-job is not a recent one - predecessors of its current form exist since 1977. The mini-job with a fixed maximum wage (of 325 euros) and lump sum social security transfers and taxes was established in 1999. In the course of the so-called Hartz reforms of 2003, the wage boundary was increased to 400 euros. Since 2013, this boundary has remained at its current level.

The number of mini-jobs was not subject to much change over the last years, consistently totaling approximately seven million (see Minijobzentrale (2017)). The number of mini-jobs in private households has increased in recent years, but compared to mini-jobs in the commercial sector they are still of minor importance. 65 percent of all mini-jobbers work solely in this form of employment (see Körner et al. (2013)). The proportion of women in mini-jobs is substantially larger than that of men: about 65 percent of all mini-jobbers are female. Students and retirees are two major groups of mini-jobbers, representing more than 40 percent of all people in this form of employment. In these two groups, however, the difference between the number of men and women is low, while among retirees the number of men in mini-jobs is even larger than that of women. As a result of the only slight difference in these groups, in the relevant group for the following discussion (people

[7] See also Haan and Prowse (2015) or Adda et al. (2017) for related approaches.

aged between 40 and 65 working solely in a mini-job) the difference between the number of men and women has to be particularly large. Therefore, the mini-job is a predominantly female phenomenon in this group. This suggests that mini-jobs in this group are especially likely to influence the pension gap.

The share of mini-jobbers with wages at or very near the upper wage boundary is large (see also Tazhitdinova (2017) for an extensive discussion). Körner et al. (2013) show that 64 percent of all homemakers with mini-jobs fully exploit the possible earnings interval. It has to be noted that the incentive to gradually increase employment hours to earnings beyond the limits of the mini-job are low, given that gross earnings greater than the mini-job boundary will initially lead to lower net income due to disproportionately increasing social security contributions. Due to German tax regulations, this income decline is, as shown by Steiner and Wrohlich (2005b), particularly severe for married persons while singles face this problem to a much lesser extent. As the share of married individuals in the discussed group is particularly large, the problem caused by the mini-job boundary is additionally exacerbated. And as pension payments in the German statutory pension scheme are directly proportional to the earned income (see, for example, Boersch-Supan and Wilke (2004) or Chapter 2 for further information), mini-jobs are often seen as treacherous with respect to a person's economic stability after retirement. Regular full - or at least part-time employment - is considered as highly beneficial in the long run and guarantees economic independence at an older age.

4.4 The model

The objective of the model[8] is to forecast the development of the gender pension gap in Germany up to the year 2038 and to describe the influence of mini-jobs on the size of this gap. To achieve this goal a two-part model consisting of a dynamic micro-simulation to predict employment biographies of those between 40 and 65 years old until their retirement and a simulation of the aging of the retired cohorts has been developed:

Based on the data of the SOEP (for further information on the data, see below), the connection between individual characteristics (like employment experience or age), transitions between the states 'full' and 'part-time employment', 'mini-job', and 'not employed' are separately estimated for men and women with and without migration background in multinomial logit models. In additional panel estimations the determinants of working hours and wages are examined. Based on these estimation results, the employment biographies are iteratively updated until the retirement age is reached. In the course of this updating process, transitions between the four states occur based on the predicted

[8]The model is developed and implemented in Stata and consists of approximately 6000 lines of code.

transition probability and a chance outcome (see also Chapter 3). If a regular employment or a mini-job is assigned to this person, working hour and wage are also calculated. Afterward, all explanatory variables are updated in order to serve as the basis for the prediction of the next period. However, additional information is needed - namely that on the number of earning points achieved before the start of the prediction period. This is achieved matching the SOEP model with the *Versicherungskontenstichprobe* (VKST), and allowing a calculation of the gender pension gap for each retiring cohort.

Based on ASID data (for more information, see below), the aging process of the current retirees is modeled. These cohorts are aged according to their age- and sex-specific survival/mortality rates as provided by the German official statistic (see Statistisches Bundesamt (2017) and Section 4.4.3).

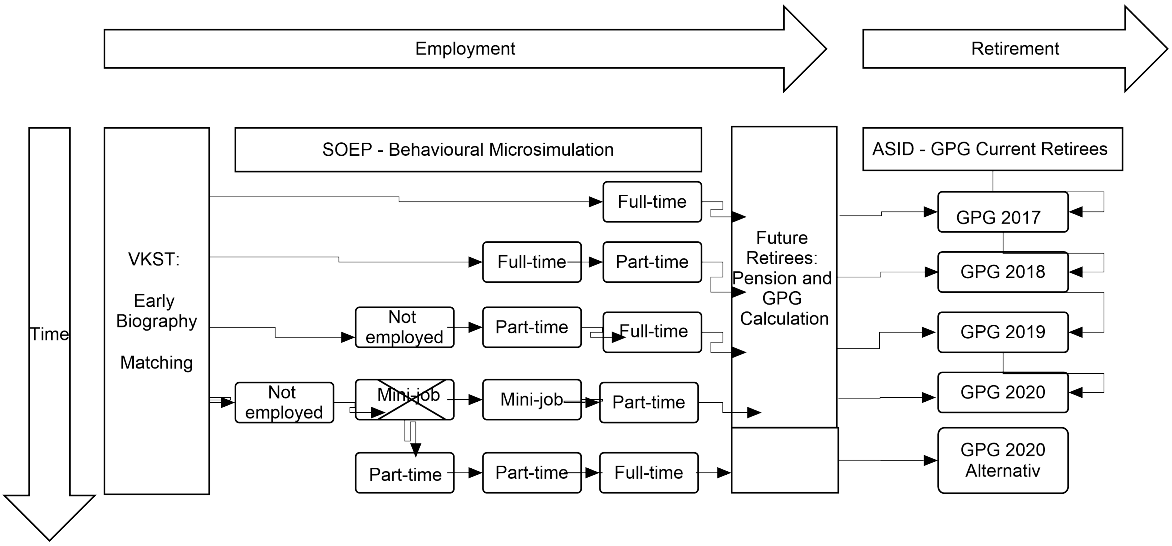
To receive the pension gap for the entire retired population at any point of time in the projected future, the results of these two models (for the currently retired population as well as for those of working age at the start of the prediction) have to be combined. At the beginning of the projection, the pension gap is entirely determined by the currently retired population as provided by the adjusted (see Section 4.4.3) ASID data. In the first year of the projection, two aspects will come into play: Firstly, the ASID population is aged by one year and cohort sizes will change as determined by sex- and age-specific mortality rates (Statistisches Bundesamt (2017)). Secondly, the oldest cohort from the employment projection model will retire. Therefore, the overall pension gap for the entire elderly populations is determined as the weighted average of the gender pension gaps of this newly retired cohort and the gap of the aged retired cohorts at the start of the projection. Equivalently, in the second year of the projection, a second cohort (as modeled by the employment projection simulations) will retire and all older cohorts (one from the employment projection model that retired the year before as well as the cohorts that were retired at the beginning of the projection) are again aged in accordance with their survival rates.[9] As before, the gender pension gap can then be calculated as the weighted average of the gaps of all cohorts of the retired population at this point in time of the projection (which now consists of two projected cohorts from the SOEP-model as well as the aged ASID-population). Consequently, as time passes, the influence of the cohorts originating from the employment projection model will be increasingly important when the overall gender pension gap of the entire elderly population in a specific year within the projection horizon is determined.

Figure 4.1 provides a schematic illustration of the overall functionality of the model as well as on the used data - all aspects of the model are described in further detail below. As a chance element

[9]The age- and sex-specific survival rates as assumed to be unchanging over the projection horizon

is involved in the prediction of the future employment biographies, the entire updating process is repeated 100 times.

FIGURE 4.1
Schematic illustration of the model



Source: Own illustration

The mini-job scenario only changes the future as the role of the mini-job can only be changed by future or current political measures. In the scenario the projection of the employment biographies is altered in such a way that all mini-jobbers are assumed to shift to a regular part-time employment. This switch from mini-job to part-time work does not only alter that very period, but will change the prediction of the entire remaining employment biography due to the change in initial conditions. The outcome of this alternative scenario is compared to the baseline result.

In the following, the relevant data-sets that are used to capture the described tasks will be briefly introduced. Afterward, the basic model as described in Chapter 3 will be explained, and then all necessary extensions to the basic model will be described in detail.

4.4.1 Data

Three data-sets are necessary to cover all aspects of the gender pension gap projection:

1. Data on old-age income of current retirees as found in the *Alterssicherung in Deutschland* (ASID) study.

2. Information on future employment periods of people of working age as available by means of

simulation based on the data of the German Socio-Economic Panel (SOEP).

3. Data on past employment of people of working age as provided by the *Versicherungskontenstichprobe* (VKST).

Each data-set will be described in further detail in the next paragraphs.

Versicherungskontenstichprobe

The *Versicherungskontenstichprobe* (VKST) of the German Statutory Pension Insurance Scheme provides the relevant information on the contributory careers of about 70,000 persons with birth cohorts between 1948 and 1985. It contains socio-demographic information (sex, age, number of children, etc.), characteristics for pension calculation (earning points, pension supply equalization, etc.), as well as biographical information on, for example, child-rearing periods.

Socio-Economic Panel

The German Socio-Economic Panel (SOEP[10]) is a large German panel data set describing households in considerable detail by providing information on employment, family, income, and social conditions. Most importantly, biographical information is also provided for periods when the respondent was not yet part of the SOEP study. Due to its start year in 1984 and its size of about 30,000 respondents, the SOEP is an extremely valuable tool to collect information on transitions during an employment biography.

Alterssicherung in Deutschland

Since 1986, every three or four years the research institute TNS Infratest conducts the survey *Alterssicherung in Deutschland* (ASID) on behalf of the German Federal Ministry of Employment and Social Affairs. The approximately 30,000 respondents of the ASID are older than 55, and are asked in great detail about their current income and its components (especially pensions) as well as their socioeconomic characteristics. The ASID provides all the necessary information to calculate the gender pension gap for the first pillar of the German pension system for current retirees (see, for example, Kortmann and Halbherr (2008)).

[10]See also Wagner et al. (2007).

4.4.2 The employment projection model

Even though substantial extensions are necessary, the behavioral micro-simulation model of Chapter 3 constitutes the basis for the gender pension gap projection model. The main task of the model is to project employment biographies until retirement. Based on SOEP panel data, the determinants of beginning, ending, or changing the type[11] of an employment are estimated depending on various individual characteristics - separately for men and women with and without migration background. Based on these estimates, the likelihood of a change in the employment status is calculated. On the basis of a chance outcome and the predicted probabilities, the employment status for the next period is determined. If employed, the number of working hours and the wages are predicted. Additionally, all relevant information (working experience, age, etc.) is updated based on the estimates of the employment situation of that period. This updating process is repeated for each individual until the retirement age is reached.

Estimation of transitions between employment states

In the previous model (see Chapter 3), only two transitions - namely those in and out of employment - were discussed. These transitions were estimated with the help of logit models. In order to capture the more complex nature of the transitions as result of additional states (mini-job, differentiation between full- and part-time work), the standard logit approach is no more feasible and a multinomial logit (see, for example, Greene (2003)) has to be used to capture the transitions. In total, the transitions between four states ('full-time employment', 'part-time employment', 'mini-job', and 'not employed') are estimated via:

$$P(Y_i = m) = \frac{\exp\left(\beta_0 + \sum_{k=1}^{K} \beta_{mk} X_{ik}\right)}{1 + \sum_{h=2}^{M} \exp\left(\beta_0 + \sum_{k=1}^{K} \beta_{hk} X_{ik}\right)} \tag{4.1}$$

The above equation is used for states two to four, while for state one

$$P(Y_i = 1) = \frac{1}{1 + \sum_{h=2}^{M} \exp\left(\beta_0 + \sum_{k=1}^{K} \beta_{hk} X_{ik}\right)} \tag{4.2}$$

holds. The inclusion of both full and part-time work is reasonable - especially when reentering employment, the choice between these two forms of employment is often important. Due to the increased importance of migration, the model is extended further and now not only allows for separate estimations for the sexes but also differentiates between the migration history (with or without a migration background). This leads in total to the estimation of sixteen transition equations - for four previous states, for two sexes, and for two migration states. Like in the earlier model, the predicted proba-

[11] For example from a mini-job to part-time work.

bilities form the basis to determine the changes between the four states. Based on the outcome of the draw of a random variable distributed uniformly between zero and one, an individual will change the employment status (e.g., being out of employment after a mini-job in the previous period) or not (stay in a mini-job).[12]

Determinants of Working hours

The size of the factors determining the number of weekly working hours h are estimated separately for men and women as well as for part- and full-time employees in linear random effects panels data models (relying on the assumption that explanatory variables and individual heterogeneity are uncorrelated):

$$h_t^i = c + \beta X_{t-1}^i + \mu_t + \nu_i + \epsilon_t^i \tag{4.3}$$

h_t^i stands for the working hours of individual i in period t. c is the constant and X_{t-1}^i are the explanatory variables of the working hours estimation equation. The explanatory variables enter this equation as first lags to avoid potential endogeneity issues. μ_t and ν_i represent year- and individual-specific heterogeneity while ϵ_t^i is an independent standard-normally distributed error-term.

As before, the set of independent variables consists of employment experience, number and age of children, education, and further factors (the specifications and the estimation results are shown in Appendix C). Mini-jobs are, for reasons discussed in the next paragraph, not included in the working hours estimations.[13]

Modeling of Wages

Estimation and projection of wages are carried out separately for regular forms of employment and mini-jobs as mini-job wages exhibit distinct patterns (see below) that have to be taken into account:

The hourly wage rates of all individuals with a part- or full-time employment are estimated in a two-step procedure. In a first step, the yearly rate of change of the average wage is estimated separately for men and women by means of first-order auto-regressive models. In a second step - and analogous to the estimation equations for the working hours - the relative deviation of the hourly wage rate dev_{hw} from the average hourly wage $\bar{hw}$ is regressed on individual characteristics determining the

[12] The regression results are shown in Tables C.1 to C.16 in Appendix C.

[13] The regression results for the determinants of working hours are shown in Tables C.17 to C.20 in Appendix C.

wage rate (education, employment experience in part- and full-time, etc.) in a random effects linear panel data framework. These regressions distinguish between the sexes as well as between full- and part-time employment.[14] Combining all the above results, we receive the monthly gross wage gw for full- and part-time employees of:[15]

$$gw_i^t = emp_i^t * h_i^t * \bar{hw}_t * (1 + dev_{hw,i}^t) * 4.34 \tag{4.4}$$

The distribution of the mini-job wages exhibits a particular pattern: a large fraction of the wages is clustered at the upper income boundary of currently 450 euros (see, for example, Tazhitdinova (2017)). This suggests that the decision to choose a wage at the upper boundary is distinct from the considerations in the remaining mini-job-interval. It is therefore necessary to capture this characteristic in the modeling of the wages. To achieve this goal, wages from mini-jobs are excluded from the standard wage finding procedure and are directly modeled and estimated in a one-inflated-beta regression (see Ospina and Ferrari (2012), for discussion on the implementation in Stata, see Buis (2010)). To use the one inflated beta regression, in a first step (and only for regression purposes) the wages between zero and 450 euros are normalized to the unit interval. The model assumes that the wages w of the mini-jobbers with a wage under 450 euros follow a beta distribution with parameters μ and ϕ:

$$f(w;\mu,\phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} w^{\mu\phi 1}(1-w)^{(1-\mu)\phi-1}, 0 < w < 1 \tag{4.5}$$

with $\phi > 0$, μ between zero and one and Γ denoting the gamma function. Incorporating the inflation factor in the regression, one ends up with the following mixture distribution:

$$f(w;\pi_1\mu,\phi) = \begin{cases} (1-\pi_1)f(w;\mu,\phi), 0 < w < 1 \\ \\ \pi_1, w = 1 \end{cases} \tag{4.6}$$

Based on the regression results[16] , the projected wages are predicted in several steps: First, the predicted probabilities for an outcome of one - meaning a wage of exactly the mini-job boundary - are calculated. Given the outcome of a uniformly distributed random variable on the unit interval, an income of 450 euros is either assigned or not. If the wage of the upper boundary is not assigned, the conditional predicted probability of a wage between zero and less than this upper boundary provides the wage prediction for this group. Throughout this analysis, it is assumed that the mini-job boundary will grow - at least approximately - with the same rate as the overall wages.

[14]For estimation results, see Table C.21 and Table C.22 in Appendix C.
[15]The average month has 4.34 weeks.
[16]Shown in Table C.23 and Table C.24 in Appendix C.

Projection of biographies

The above estimations as well as a person's characteristics are used to iteratively update employment status, working hours and wages for each individual in the sample. In a first step, the propensities for a transition from and to each of the states 'not employed', 'mini-job', 'part-time employment', and 'full-time employment' are predicted and ordered consecutively. Based on the outcome of a uniformly distributed random variable on the unit interval, the state for the next period is assigned.[17] If an employment is predicted for the following period, working hours and wages are allocated to this person based on their individual characteristics and the respective estimation results. These predictions can be used to update the personal characteristics that now form the basis for the next updating step.[18] By continuing this process, all biographies are iteratively updated until the retirement age is reached.

4.4.3 The gender pension gap projection model

Several extensions and adjustments became necessary to analyze the long-term development of the gender pension gap and the impact of mini-jobs, as well as to further improve the behavioral micro-simulation model:

- Projection of the gender pension gap for current retirees based on ASID data.
- Matching of SOEP and VKST to incorporate past earning points.
- Adjustment of the data to factor in the most recent information.
- Incorporation of the pension system.
- Aggregation of results and long term development of gender pension gap.

All these aspects are discussed in the following sections in greater detail.

Projection of the gender pension gap for current retirees

The future development of the gender pension gap will naturally depend on the gap between current retirees and its development. Chapter 2 suggests that the pension gap in the statutory pension

[17]Assume, for example, that a person is employed in period t and that the predicted probability for remaining employed, predicted based on regression results and personal information, is 70 percent. Assume further that the likelihood to end this employment as well as to switch to part-time work or mini-job each amounts to ten percent. Based on these predictions, one specific interval is assigned to each state - 0 to 0.7: full-time employment, 0.7 to 0.8: not employed, 0.8 to 0.9: part-time work, and 0.9 to 1: mini-job. If the chance draw from the uniformly distributed random variable is 0.63, the state 'full-time employment' is assigned to this individual in period t as the chance draw falls into respective interval.

[18]In the above example, the individual now possesses an additional year of full-time employment experience. This will, ceteris paribus, increase the likelihood of remaining employed in period $t+2$.

scheme amounts to approximately 57 percent, where more evidence is presented that suggests the gender pension gap has been decreasing in recent years. This indicates that the gap is smaller for younger cohorts and hence the gap of the current retirees will decline due to the aging process of this group, since the age-specific death rate will be higher for older individuals. Simultaneously, the overall size of this group will decrease and its influence on the overall gap development will diminish as increasingly more current employees retire.

In order to conduct this projection, in a first step, the average age-specific pension income and the size of each age-cohort are calculated. Then, the projection process is done by means of static aging (see, for example Sutherland et al. (1999) or Li et al. (2014) for extensive discussions on modeling population changes) based on the age and sex-specific death rates provided by the German Federal Statistical Office (see Statistisches Bundesamt (2017)). This leads to a shrinking of the cohort sizes in accordance with the sex-specific death rates and thereby to an adjustment process of the gender pension gap. While it is well known that death rates will depend on other factors beyond sex and age (see, for example, Chetty et al. (2016) for a recent discussion on the relationship between wealth and life expectancy in the US), those are not included in the projection, given that they would only substantially alter the results if the size of these effects significantly differs between the sexes. As expected, the aging leads to a distinct reduction in the gender pension gap for the current retirees within the prediction horizon. In order to take the fact into account that the data of the SOEP is more recent compared to that of the ASID, the average pension incomes of men and women from the ASID are predicted for a sufficient time period to be compatible with the SOEP (see Hamilton (1994) for a general discussion of time series models).

Matching of SOEP and VKST

The data of the German Socio-Economic Panel (SOEP) serves as the basis for the prediction of the employment biographies; however, it does not contain information on the number of earning points an individual has received up to this point. The *Versicherungskontenstichprobe* (VKST), on the other hand, does contain detailed information on the number of earning points but is not well-suited for forecasting employment biographies. Both parts are, however, needed to predict the gender pension gap. For this reason, individuals from both data-sets with similar characteristics are matched to serve as one case in the further proceedings. Therefore, it is necessary that the data-sets share common and comparable variables. With SOEP and VKST this is straightforward, as they share information on socio-economic characteristics like age, sex, education, income, and marital status.

Matching techniques have their origin in the work of Donald Rubin (see Rubin (1973) or Rosenbaum and Rubin (1983)), and since then numerous approaches have been introduced (a good introduction to matching methods can, for example, be found in D'Orazio et al. (2006)). In the context of the fusion of data-sets, often methods like propensity score or k-nearest-neighbor matching are used (see, for example, Rässler (2002) for details). Those matching algorithms are, however, not without issues as they can rely on severe assumptions (like the conditional independence assumption - see D'Orazio et al. (2006), Chapter 2) or may be facing problems concerning the similarity of matched observations when many matching variables are used (the so-called curse of dimensionality - see Marimont and Shapiro (1979)).

Iacus, King, and Porro (see Iacus et al. (2012)) propose a straightforward alternative approach[19] based on matching observations within predefined groups (called coarsened exact matching). Following and adapting Iacus et al. (2012), both data-sets are divided into groups with similar characteristics (age, employment experience, region, household types) and matching is only performed for exact matches in the respective groups. When more than one exact match is available within a group[20] the matching is conducted purely at random. To account for the randomness in the matching process, the matching by chance within a group is repeated independent of the previous matching for each simulation run. For baseline and alternative scenarios, however, the same matching is always used. This proceeding accounts for the uncertainty in the matching process in a fashion similar to multiple imputation in an imputation context (see Rubin (1987)). This approach guarantees that only individuals with reasonably similar attributes are matched.

Data adjustment

The micro-simulation model uses data from various sources - SOEP, ASID, and VKST. All three data-sets come from different years and none of them is of 2017. There is, however, data available that provides extremely recent information on employees and retirees (e.g., with respect to their number and age), often originating from official sources (and thus very reliable). It is the goal to adjust the weights of the data-sets in such a way that they incorporate this recent information. There is

[19]Though in the context of causal inference.

[20]All groups are kept large enough that this holds true. Consequently, different matches are always available. Therefore, obviously, at no time identical individuals can be matched as both data sets contain different persons and even if this was not the case, the respective groups are large enough that no specific individual could be identified. This approach has, however, an advantage over just assigning the group means in the number of earning points of the VKST to the SOEP population because such a proceeding would underestimate the uncertainty of the prediction. Therefore, in all simulation runs a different matching is chosen.

a variety of approaches to do so, ranging from relatively straightforward algorithms (for example, the RAS algorithm - see Bachem and Korte (1979)) to very complex methods. Following Merz (see Merz (1991)), this chapter uses micro-data adjustment by means of the Minimum Information Loss Principle (MIL) to achieve a representative data-set that is compatible with recent developments. In doing so, it is the intention to reweigh the data in such a way that it is guaranteed that the projection process starts with the most recent boundary conditions while altering the original weights as little as possible.[21] In particular, the data-set is adjusted with respect to the current number of mini-jobbers (differentiated by sex; see Minijobzentrale (2017)), the age, and pension income distribution for those receiving pensions from statutory pension scheme (see Rentenversicherung (2017)), as well as the sex and age distribution of the German employees (see Statistisches Bundesamt (2016b)).

Pensions and accumulation

The statutory pension scheme constitutes the by far most important part of the German pension system, covering the vast majority of Germany's employees. Additional private schemes (like the so-called *Riester-Rente*) have gained in importance (see, for example, Geyer (2011)), but their significance has not even remotely reached that of the statutory pension scheme. For this reason, this study focuses on this pension scheme. The pension from this most significant pillar of the pension system relies heavily on the number of earning points received during a person's employment life. An individual can receive approximately up to two earning points in each year of employment. The exact number of points is determined as the ratio between a person's income and the average. Consequently, an average earner will receive exactly one earning point per year.

In the simulation model, the number of earnings point achieved during and before the prediction period can be endogenously determined within the model as it projects a representative sample of the individual employment biographies. For this reason, the model can be used to calculate the society-wide average wage and therefore the number of earning points for each individual and projection year. The VKST provides the information the number of earning point from periods before the start of the prediction. Throughout the projections, it is assumed that men and women retire at 65 and that the age factor in pension calculation is therefore 1.0. Since men and women, on average, retire at about the same age (see Rentenversicherung (2017)), this assumption is not a crucial one, given that the interest focuses on gender differences.

[21] See, for example, Wagner et al. (1991) for information on the data adjustment process of the SOEP.

4.5 The projected gender pension gap

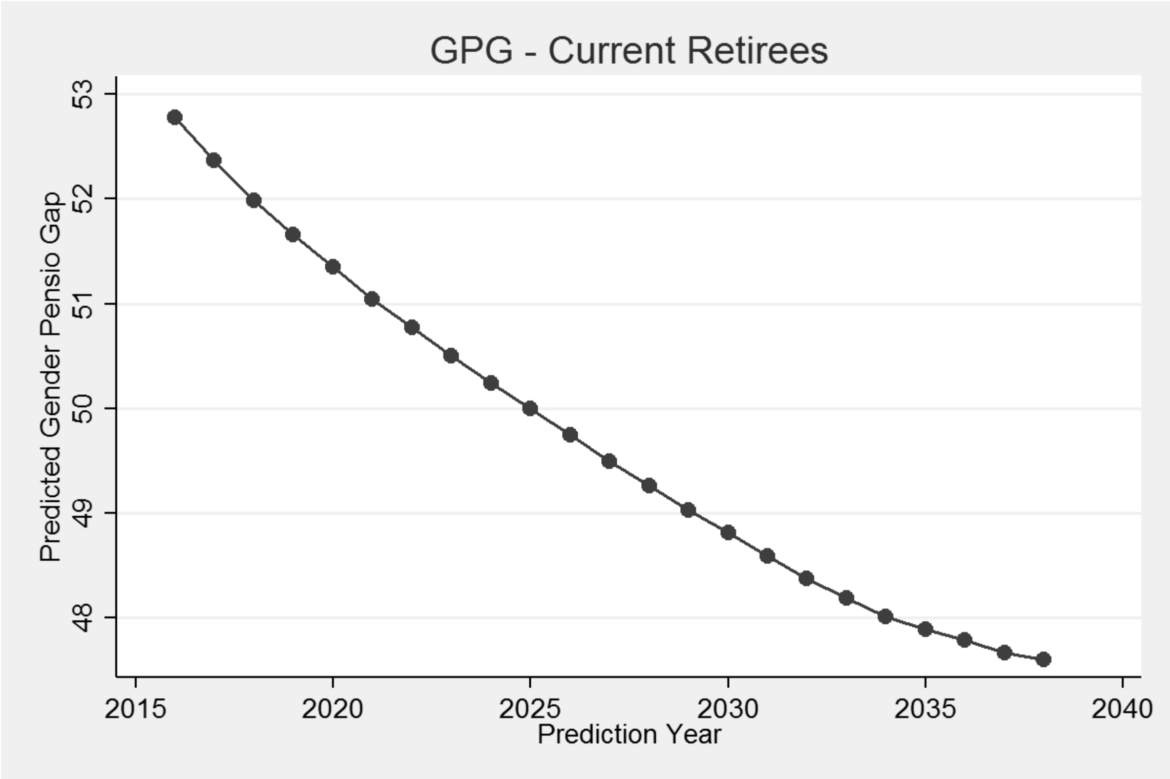
In the following section, the baseline projection of the gender pension gap until 2038 - a projection of an additional 20 years after the current date - is introduced. The data used in this projection is adjusted to the latest available marginal distributions. Most of these distributions date back to 2016. In particular, the data is adjusted to the number of employees sub-classified by age and sex, the number of pensioners (divided by age and sex) in the statutory pension scheme as well as the number of mini-jobbers in a similar differentiation (see Minijobzentrale (2017)). Hence, the projection starts with the year 2017. As described above, this model does not intend to project the entire pension gap but focuses on the most important pillar of the German pension system - the statutory pension scheme. In order to avoid modeling transitions in and out of the statutory pension scheme (for example, by becoming self-employed), this approach makes the simplifying assumption that the self-employed in the last year with actual data which do not contribute to the statutory pension scheme will continue not contributing in the future.

It is the final goal of this section to predict the overall gender pension gap until 2038. To do so, the gaps for the current and future retirees are calculated, presented and discussed separately at first. Based on these results, the gender pension gap of the entire retired population is calculated as the weighted average of the gaps of both groups (see Section 4.4 for details on the functioning of the model).

It is known gender gap in many areas of the German pension system - like statuary, occupational or individual pension schemes - well exceeds 50 percent. Consequently, the overall German gender pension gap currently is of similar magnitude. Previous studies show that the gap in statutory pension scheme is the smallest among the pillars of the German pension system (see Hänisch and Klos (2014)). In Chapter 2, a gap estimate of 57 percent can be found for this pillar. After adjusting the ASID data to 2017, a gap of approximately 52 percent remains (see Figure 4.2), indicating that the gender pension gap of the current pensioners will be constantly decreasing. This finding is in line with the expectations discussed in Chapter 2. Figure 4.2 also illustrates that this decline will proceed in the projection period. The decline is almost linear and only slightly decreasing in speed after 2030. The decrease of the gap for aging pensioner cohorts reveals that the gender pension gap is smaller for younger retirees. It is therefore apparent that the gap in 2038 of about 47 percent should be similar to the gap of today's youngest pensioners.

Figure 4.3 depicts the gender pension gap of the retiring cohorts between 2017 and 2038. The gap amounts to about 47 percent for the retirees of 2017. This is very similar to the gap of the youngest

Figure 4.2
Predicted gender pension for current retirees based on ASID data

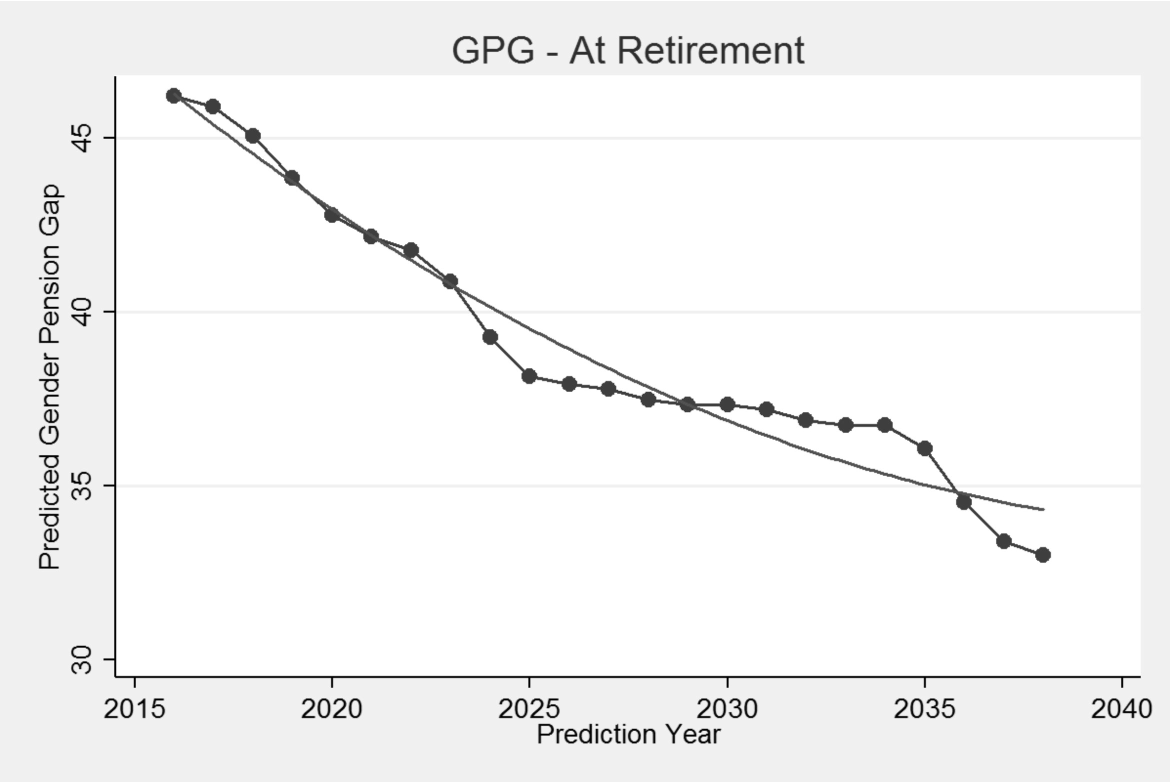


Source: ASID, own calculations

current retirees as shown above and provides evidence that the part of the model based on SOEP and VKST and the part based on the ASID are consistent. Despite of some erratic movements in Figure 4.3 due to prediction uncertainty and relatively small sample sizes, a steady decrease in the pension gap can clearly be observed in the long-run. This decrease is especially pronounced for the years up to 2025, suggesting a particularly strong harmonization process in employment behavior and wages of men and women approximately born between 1950 and 1960. The gap continues to decrease after 2025 - albeit at a smaller rate - and only picks up some pace in the very last years of the prediction to finally reach 34 percent in 2038. It is apparent that gender pension gap for the retiring cohorts will not - and cannot - have closed by 2038, as they reflect the past and current situation in the labor market with, for example, a gender pay gap of approximately 21 percent. Nevertheless, a projection can only be based on currently available information, and it is thereby evident that this trend can be altered by future developments and policies. This chapter lays emphasis on the role of the mini-job in affecting the gap. Also other policies, however, like improved day care for young children (see, for example, Haan and Wrohlich (2011)) could be effective.

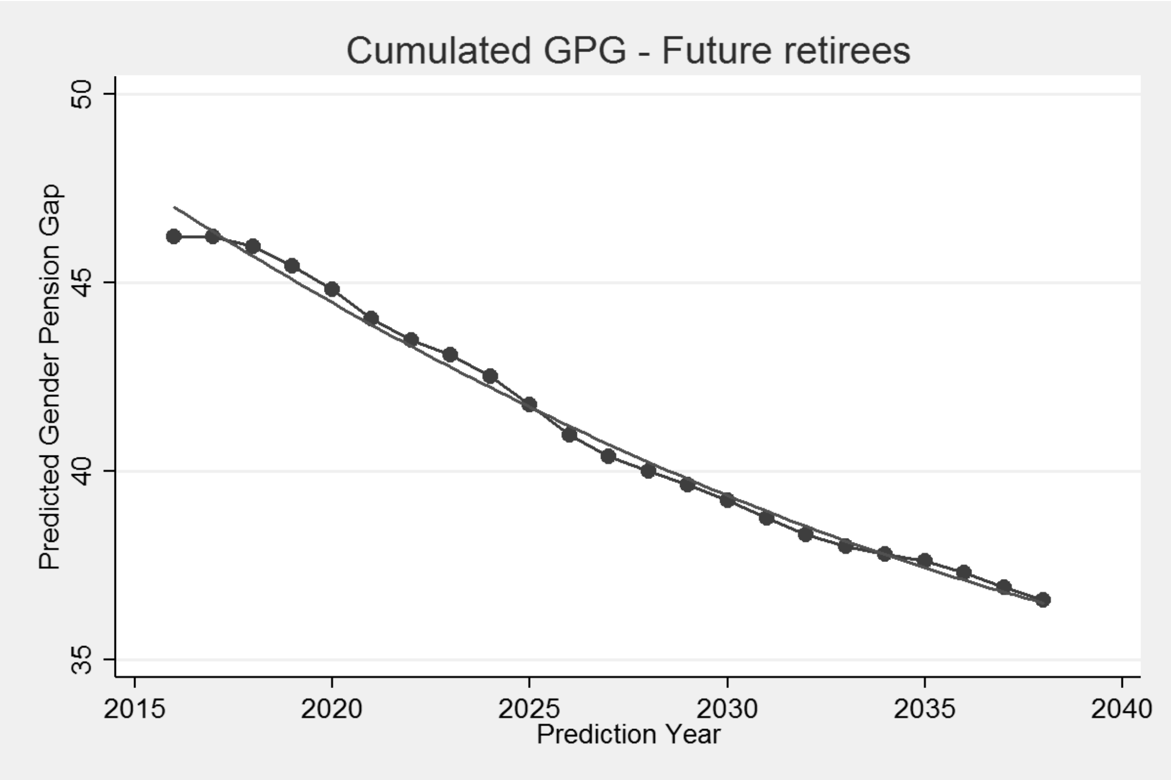
The cumulated development of the gender pension gap for all future retirees can be seen in Figure

Figure 4.3
Predicted gender pension at retirement for future retirees based on SOEP and VKST data (solid line: quadratic trend)



Source: SOEPv29, VKST, own calculations

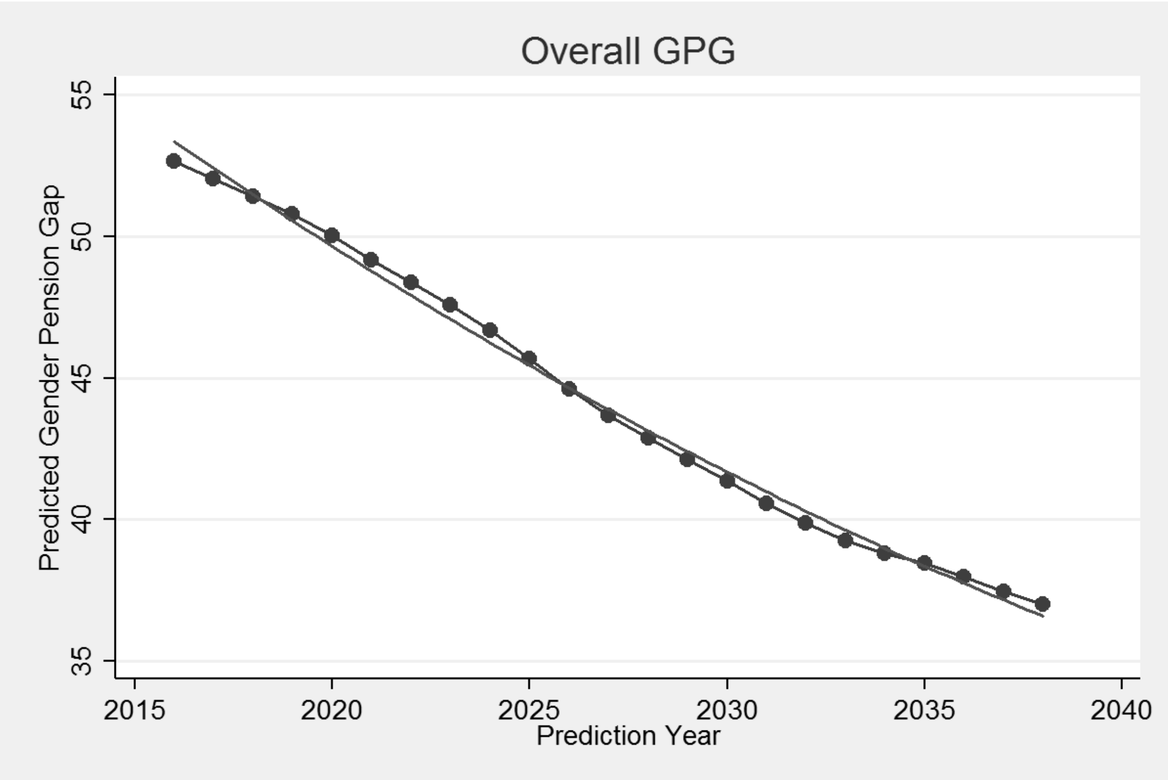
Figure 4.4
Predicted cumulated gender pension for future retirees based on SOEP and VKST data (solid line: quadratic trend)



Source: SOEPv29, VKST, own calculations

4.4. This development reflects the progress of the gender pension gap of the retiring cohorts as seen above. The cumulated gap starts out at about 47 percent - which naturally corresponds to the gap of the retiring cohort in that specific year. Afterward, a slow decrease of the gap to a level of about 37 percent can be observed. Due to the accumulation of the gaps at retirement, the movement of the gap is smoother and ends at a 37 percent level instead of a 34 percent one.

FIGURE 4.5
Predicted overall gender pension gap based on ASID, SOEP and VKST (solid line: quadratic trend)



Source: SOEPv29, VKST, ASID, own calculations

Figure 4.5 finally depicts the predicted overall development of the gender pension gap. It can be seen the overall gap is expected to be decreasing from a little more than 52 percent (the gap of the current retirees) to about 38 percent by 2038. The speed of the reduction is slightly decreasing after the mid 2020s. This trend is perfectly in line with the recent development of the gender pension gap from all pillars. Even though it was not known before at which rate the gender pension gap is expected to decrease, the fact that the gender pension gap will decrease might not be unexpected. It is, however, also evident that the gender pension gap will be far from having been vanished by 2040. The effects of the current gender pay gap as well as differences in the employment biographies between the genders will be clearly noticeable by this time.

Naturally, the question arises to what degrees policies can influence the gender pension gap. It is obvious that no policy can immediately decrease the gap unless measures are taken to change the pension system itself. Policies that, for example, encourage additional employment of women can only be successful in the long run as for cohorts nearest to retirement the pension income is already almost entirely determined. It is nevertheless important to ask which policies are adequate towards at least partially closing the gender pension gap within the next 20 years. It is well known that mini-jobs negatively affect the individual pension income. It is, however, unknown whether this negative effect will also come into force on an aggregate society-wide level and will significantly change the gender pension gap in the long run. The following section discusses this question.

4.6 Scenario results: The mini-job and old-age inequality

Again and again, the importance of a regular employment is emphasized in the political and public discussion. Mini-jobs are seen as highly critical with respect to economic stability and independence in old age due to the low pension scheme contributions as a result of the low wages. Furthermore, the incentives to increase one's employment hours beyond the mini-job threshold are rather slim, given that net wages beyond this threshold will initially drop.[22] But an average part-time employment would constitute a serious improvement of the economic situation in old age due to the substantially higher pension scheme contributions. Moreover, the chances of a switch to full-time work would be substantially higher (see Appendix C or Statistisches Bundesamt (2014)).

In this scenario, it is therefore assumed that in each case in which a mini-job is projected by the model, a part-time employment is supposed to be chosen instead.[23] As a result, a higher number of working hours and higher wages are allocated to the affected individuals. It is important to note that this scenario does not simply exchange periods of mini-jobs with those of part-time work - instead, entire employment trajectories are changed due to differing starting conditions. Employment biographies will emerge differently.

While the negative effects of mini-jobs on the individual level are undoubted, it is unknown how large its society-wide impact will be. Particularly, it is not understood how significant the role of the mini-job in keeping the gender pension gap open really is. The hypothetical abolition of the mini-job provides evidence on its society-wide long-run effect on the gender pension gap. One has to keep in

[22] As of 2017 a gross wage of 450 euros will result in a net wage of 450 euro. When pension scheme contribution are chosen, the net wage still amounts to 433.35 euros. A gross wage of 451 euros, on the other hand, will lead to a net income of only 381.35 euros.

[23] As in Chapter 3, the model is not designed as a general equilibrium model. Throughout the chapter, it is therefore assumed that additional labor supply finds the respective demand.

mind that employment decisions of the past are not altered such that an initial reaction of the gap cannot be expected.

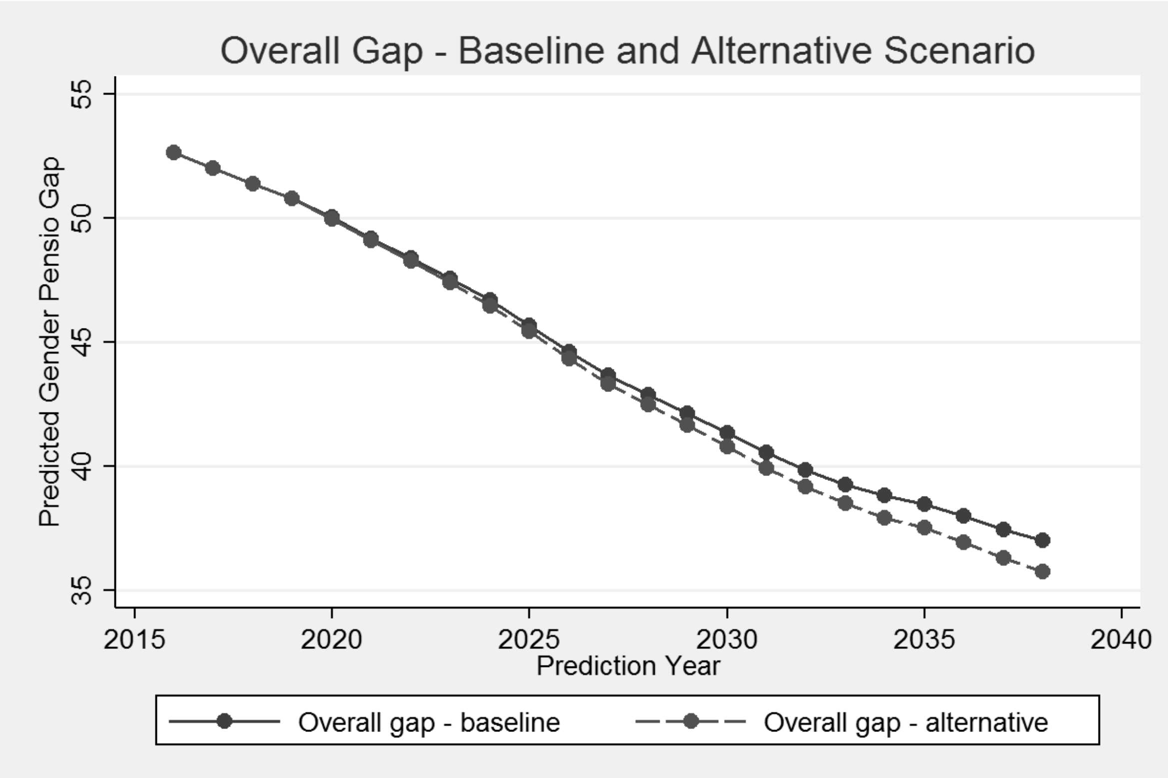
It is irrefutable that no political measure could affect all current and future mini-jobbers in a way that they will choose part-time work instead. For this scenario to happen, beyond legislative measures, changes in preferences would have to occur and all necessary prerequisites (for example with respect to the availability of care for children or elderly relatives) would have to be met. Nevertheless, the scenario helps depict the maximum potential effect such a change in employment forms can have as well as providing insight in the role of the mini-job in the formation of the gender pension gap. Alternatively, a scenario in which also past mini-job spells are altered to a regular part-time employment could be considered. This would potentially provide a more immediate picture on the current effect of the mini-job on the gender pension gap. This scenario, however, seems to be less relevant from a practical perspective, while the chosen one is much more feasible even though an attempted implementation would most likely not lead to the maximum possible effect as described in this scenario. Additionally, the scenario is revealing with respect to the speed of action of a reform on a measure that is predetermined with such a long fore-run, like the gender pension gap which is by itself of relevance.

The effects of this scenario on the model are diverse and complex. First and foremost, the change in the income of previous mini-jobbers will change the society-wide average income and thereby the received earning points for the entire population (for details see, for example, Chapter 2). Two aspects are important in the discussion of the scenario. Firstly, wages and working hours for the previous mini-jobbers are assigned in accordance with their individual characteristics (like education or employment experience). It is thereby guaranteed that reasonable wages will be assigned even though the employment type has changed. Secondly, the entire employment biography will change due to the switch from mini-job to part-time work reflecting the estimated differences in the employment behavior between the employment forms (see also Appendix C).

Figures 4.6 and 4.7 highlight the differences between the baseline and the alternative scenario - meaning the change of the gender pension gap as result of choosing a part-time employment instead of a mini-job. Figure 4.6 shows the development of the gender pension gap in both scenarios in absolute terms. Figure 4.7 depicts the difference between the scenarios.

Figure 4.7 shows the slow decrease in the gender pension gap until the end of the projection horizon

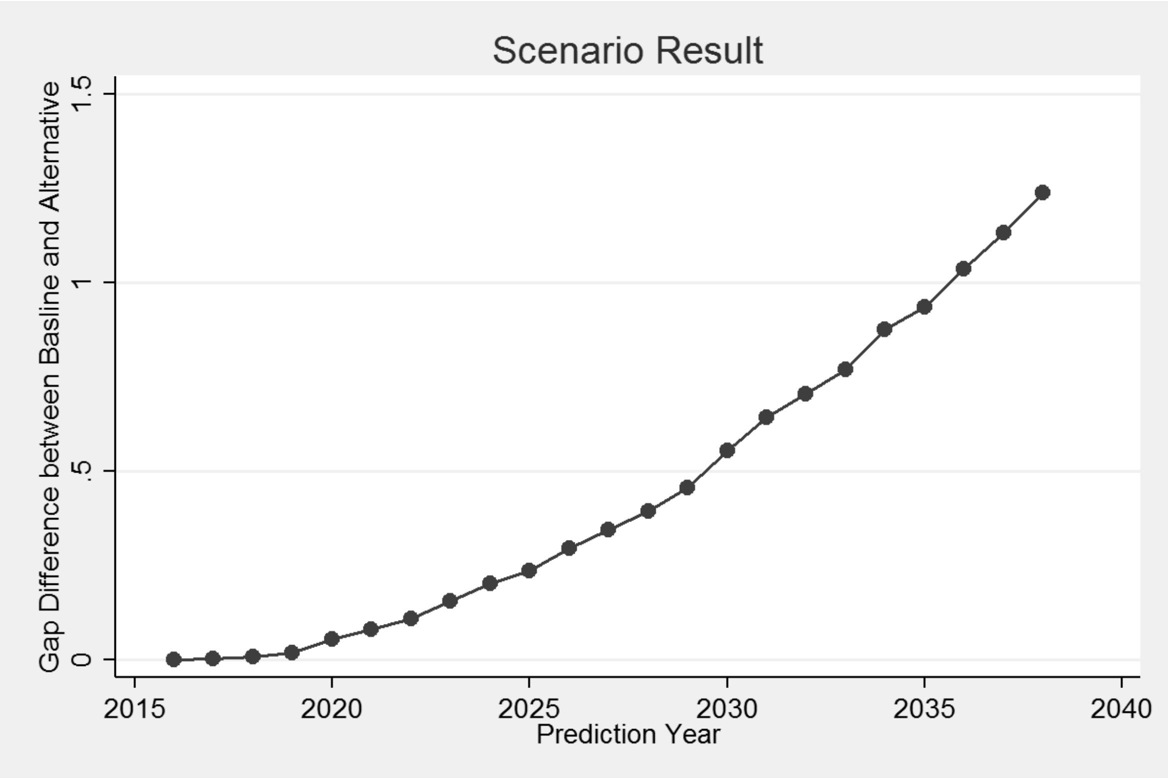
Figure 4.6
Predicted development of the gender pension gap in baseline and alternative scenario



Source: SOEPv29, ASID, VKST, own calculations

in 2038 as a consequence of the assumed change in employment behavior. As expected, there is almost no initial reaction in the gender pension gap, since almost nobody among the retirees is affected from the scenario. Given that the choice of a mini-job right before retirement is relatively uncommon (see Körner et al. (2013)), the gender pension gap only slowly decreases as the number of affected cohorts rises. More mini-jobbers will, however, be in the younger cohorts of the sample, leading to a speeding up in the decline of the gender pension gap from the middle 2020s onwards, as the simulation suggests. Finally, a gap decrease of a little more than one percentage point (about 1.3 percentage points) can be observed. This constitutes the overall maximum effect of the scenario on the gender pension gap within the projection horizon. It has to be noted that the building up processes of the consequences of the scenario is by no means finished. As increasingly more cohorts whose complete employment biographies were influenced by the scenario assumptions retire, the gap will further decline. Therefore, these findings suggest that the choice of a mini-job that is predominantly made by women has an influence on the size of the gender pension gap that is certainly not negligible. But it can also clearly be seen that any political process trying to abolish the mini-job will affect the closing of the gender pension gap only in a slow and laborious manner.

FIGURE 4.7
Difference between baseline and alternative scenario



Source: SOEPv29, ASID, VKST, own calculations

Robustness checks have been carried out in several ways: different specifications were chosen in the transition as well as in the wage equations, and the time period used in the regression was also altered. In all cases, the extent of the impact of mini-jobs on the gender pension gap is estimated to reach between one and two percentage points.

4.6.1 Conclusion

Chapter 4 provides a connection between Chapters 2 and 3 in describing the formation of the gender pension gap in greater detail. It extents earlier approaches (see Westermeier et al. (2017) or Frommert and Strauß (2013)) and allows a prediction of the entire gender pension gap over the next 20 years. This approach is also the first to quantify scenarios - it allows to examine the size of the influence of mini-jobs on the gender pension gap and to describe the transition process of changes in employment on average gender income differences among pensioners.

To achieve these goals, chapter three's simulation model is expanded extensively. First and foremost, the state space is substantially extended and now allows for a differentiation between full-time work, part-time work, as well as mini-jobs. Therefore a methodological adjustment became necessary to cope with the increased number of states. The simulation model now uses multinomial logits instead of an ordinary logit. Due to the specific wage structure of mini-jobs, a one-inflated beta regression is chosen to examine the wage determinants. The matching of VKST and SOEP guarantees that the gap of periods prior to the start of the prediction process is taken into account. By combining these previous periods with the simulation model, the gap for the new retirees can be projected. ASID data is used to predict the gender pension gap for the current retirees and by combining the results for both current and future retirees the overall gap development is projected.

The gender pension gap is estimated to currently amount to approximately 52 percent. It is expected to decrease continuously until 2038, though the speed of this decline will be slowing down. For 2038, a level of about 37 percent is estimated. This decrease is certainly due to adjustments in education and employment between men and women. In scenarios, the long-term the influence on policies on the gap development can be determined. Here, specific focus is laid on the role of the mini-job. It is shown that a substitution of mini-jobs with regular part-time employment for all current and future mini-jobbers will close the gender pension gap by approximately 1.5 percent. This finding is indicative of two results: firstly, the mini-job plays a non-negligible role in keeping the gender pension gap open but, secondly, any political attempt to close the gender pension gap in the short run by means of changes in mini-jobs would be in vain, as the simulation is able to quantify how slow the transition process of policies really is.

Similar to Chapter 3, the model of this chapter is not a general equilibrium one - it is assumed that the predicted labor supply will find the respective demand. Certainly, the inclusion of a labor demand model in the simulation would be, though very complex and difficult to implement, a valuable extension of this approach. The chosen scenario is, for sure, not the only sensible option - one could, for example, discuss the case in which mini-jobs are also for the past replaced by a regular part-time employment. This would allow the estimation of the effect of the mini-job on the current and future gender pension gap. Nevertheless, this alternative seems not be as relevant from the practical perspective as no policy could implement such a scenario. Furthermore, the chosen scenario provides insight into the speed in which policies can be effective. Similarly, alternative methods for modeling employment biographies are possible - those range from matching models (see Westermeier et al. (2017)) to structural approaches (see Adda et al. (2017)) and possibly many other options. Surely, a comparison of these approaches with respect to their prediction accuracy would be a reasonable extension of this chapter.

Chapter 5

Conclusion

5.1 Content, contribution, and critical discussion

All chapters of this thesis focus on gender income inequality at an older age, but discuss different aspects of and different approaches to this topic. Chapter 2 looks directly at the gender pension gap and explores its determinants by means of decomposition analysis. Chapters 3 and 4 use a less direct approach and have a look at the formation process of old-age gender income differences in the course of life. Chapter 3 discusses the consequences of career interruptions on the future development of employment biographies. As women tend to interrupt their careers more often than men, such employment breaks are a major factor in generating inequality in later years. Chapter 4 examines one specific form of employment, the mini-job, and its negative consequences due to low pension scheme contributions and describes how the predicted development of the gender pension gap - the relative difference between the average own pension incomes of men and women - would change if a regular part-time work was chosen instead of a mini-job. As the mini-job is predominantly chosen by women, this form of employment can be one component in the formation of the gender pension gap.

In a broader context, all three chapters can be seen as a part of the ongoing discussion on gender inequality issues (see Plantenga and Remery (2006) or Bettio et al. (2013)). But they can as well be regarded in the context of increased worries about old-age poverty in public, political, and academic discussions (see Haan et al. (2017)) as result of demographic changes in Germany. The main interest of the previous chapters is, however, not focusing on the pure income situation instead they are, to their largest part, discussing equality, economic independence, and fairness issues. Therefore, all chapters are examining various aspects of the building-up process of inequality in the course of life. The chosen approach is an empirical and methodological one: estimation techniques, micro-simulation, as well as decomposition methods are used to capture the various aspects of the formation of gender inequality and its development during employment biographies. In the following, a very brief overview on the individual chapters and their major findings is given:

Chapter 2 analyzes the gender pension gap in Germany based on the *Alterssicherung in Deutschland* survey. The gender pension gap is defined as relative difference between the average own pension income of men and women and is estimated - for all pillars of the German pension system - to amount to 60 percent as of 2007. A constant decrease of the gap over the past decades can also be observed. To gain additional insight in the nature of the gap, decomposition analysis is used to learn more about the underlying factors that are causing this inequality. Standard Oaxaca-Blinder decomposition techniques (see Oaxaca (1973) and Blinder (1973)) show that education and employment experience are the two main driving forces of the gap. This may not come as a surprise as these findings confirm earlier research by Frommert and Strauß (2013), though their work is based on different data. It is, however, most interesting to note that the gender pension gap is not constant over the old-age income distribution and that same holds for the influence of its major determinants. The gender pension gap not only decreases for higher quantiles of the pension income distribution - the influence of employment experience on the gap diminishes and the consequences of average education disparities increase. To come to these results, non-linear decomposition techniques (see Fortin et al. (2011)) are used for the first time in the context on old-age income inequality.

Chapter 3 examines the effects of career interruptions on an average person's life-time income and thereby calculates the true mean cost of a year off. This is achieved by developing a complex micro-simulation model based on SOEP-data that is able to predict employment biographies until retirement. This is done by estimating transition probabilities between states (employed and not employed), the determinants of hourly wages, as well as those of working hours. The estimation results are used to iteratively update the biography of each individual in the sample. It can be seen that the cost of a career interruption is substantially larger than just those of one year's work. Most importantly, however, the cost of the interruption does only diminish very slowly for the average affected person. The effect of the interruption is therefore very long-lasting. Certainly, the consequences of a career interruption diminish once a stable employment biography is reached, but the likelihood of achieving such a stable biography is reduced by the interruption which in turn leads to the long-term negative consequences for the average affected person. As women are more likely to interrupt an employment, these finding directly relate to the discussion of the gender pension gap.

Chapter 4 projects the long-term development of the gender pension gap and discusses the effect of the mini-job on this gap. The mini-job is rightly seen as highly problematic with respect to a person's financial situation and economic independence after retirement. And as this form of employment is a particularly female phenomenon, the question naturally arises whether the mini-job's effects are not only negative on the individual level but whether they are substantial enough to be influential on the society-wide scale, that is whether they are contributing to keep the gender pension gap open. Therefore, the simulation model of the previous chapter is significantly extended by incorporating current retirees as well as past pension entitlements and it is thereby able to project the gender pension gap for a period of 20 years. The results suggest that gender pension gap in the statutory pension scheme will continue to decrease to a level of less than 40 percent by the end of the 2030s. Scenarios show that the mini-job has in fact a non-negligible influence on the gap (about 1.5 percentage points in 2038) but they also suggest that any political measure trying to influence the gender pension gap through popularizing regular employment instead of mini-jobs would only be working in a slow and laborious manner.

Gaps in various areas have been discussed in the literature on gender inequality but the gender wage gap is by far the most dominant one. Nevertheless, the gender pension gap is far from being just another gap. The importance of the gender pension gap stems from fact that it is not only a measure of inequality among pensioners but also, due to the nature of the German pension system, a mean to aggregate the gender differences of entire employment biographies. The wage gap, on the other hand, is merely one extract from that biography, though, admittedly, are more current one. With that said, the adopted life-time perspective in the analysis of gender differences seems to be a very reasonable choice. It is important to note that the above discussion does not predominantly focus on the monetary situation but explores the differences between own entitlements and thereby lays emphasis on the economic independence at an old age - a perspective that is, for example, also chosen by the OECD (see Plantenga and Remery (2006)) - and the aforementioned lifetime perspective.

Beside their contribution to the understanding of the formation of inequality in the course of life, the previous three chapters provide new methodological approaches to address those questions. The decomposition methods used in Chapter 2 are for the first time used in the context of old-age income. The micro-simulation model developed in Chapter 3 and substantially extended in Chapter 4, provides a new avenue for the simulation of biographies. It is, however, the case that any prediction approach like the before mentioned behavioral micro-simulation model has limitations in its ability to predict the future. Naturally, unforeseeable developments cannot be incorporated in any model and therefore all available current information can only and should be used. The simulation extrapolates this current information to provide a forecast which might be better understood as a scenario of the future based on the assumption that today's relationships and trends continue to hold. This is certainly not only a problem when projecting employment biographies - other fields are experiencing the same difficulties (see, for example, the discussion on the prediction of labor supply as presented in Zika et al. (2012)).

The approaches of Chapters 3 and 4 are no general equilibrium models - it is therefore assumed that changes in labor supply find the respective demand. The labor demand side is not modeled even though there are approaches available to model labor demand in the long run (see Drosdowski et al. (2017)). These approaches are, however, in general extremely complex and will have to rely on strong assumptions themselves such that they also have to be understood as scenario calculations. The long-term development of labor demand will depend on many factors ranging from demographic changes over economic innovations to political crises. In view of the difficulty of correctly predicting the economic development even in the short-run, it seems reasonable to avoid the much larger challenge of a long-term projection and assume that the small scenario changes do not change the economic situation too dramatically. One also has to keep in mind that the purpose of the previous two chapters is to examine gender differences and not to predict the overall economic development - an economic crisis would certainly decrease the overall labor demand but it is far less likely that this crisis will also disturb the relative differences in the economic situation of men and women. If this crisis, for example, lead to an equivalent increase in part-time work or unemployment for both genders, the relative income differences will not, at least not substantially, change.

The model is driven by empirical estimates of transitions in and out of employment, working hours, and wages and does not explicitly assume optimization behavior of the sample members. In this respect, this model is similar to other approaches - for example, the projection in Geyer and Steiner (2014) is based on the similarity of biographies and does also not rely on an underlying optimization assumption. The model has to assume that the estimated coefficients will not change in the course of the projection horizon. This simplification allows for a projection of employment biographies under the assumption that future estimates will approximately correspond to those from today. Nevertheless, the predictions for each individual will change in every single period, as personal characteristics are adjusted in the course of the updating process. A comparison of this model with one driven by optimization would certainly be of interest. Up to this point, this model is intended to be purely driven by empirical analysis and rely as little as possible on additional assumptions.

It might be seen as cause for concern that different data sources have to be used in the simulation model. However, each of the data sets is the most suitable one for its specific purpose and proper data preparation techniques (matching and data adjustment) are used to guarantee that the data captures the most recent developments. To ensure the robustness of the results, in any case different estimation techniques, sample specifications, and sets of independent variables are used.

5.2 Political applications and extensions

All chapters provide insight in the future development of the gender pension gap and its determinants during employment life and thereby empirical evidence and foresight for forthcoming political measures. Especially Chapter 4 provides information on the speed of action of reforms on a long-term predetermined measure like the gender pension gap. The results suggest that such a political measure will only be effective with a substantial delay - a delay that is quantified within the models of Chapter 3 and 4. The slow but lasting impact of policies underline the need for careful consideration before any political measure is implemented as developments once started are hard to reverse.

The results clearly show the positive effects of policies encouraging education. Gender disparities in education have, however, at least in broader context vanished by 2017 but nevertheless specific choices like those of field of study or occupation may still be contributing to the gender wage gap (see Weichselbaumer and Winter-Ebmer (2005)) and thereby prohibit the gender pension gap from closing within a foreseeable amount of time. Differences in employment are still present - with respect to both employment rates as well as working hours - but strong alignment processes are also noticeable. Increases in child-care opportunities, for example, have substantially improved the opportunities - particularly of women - to participate in the labor market. This process certainly contributes to the closing process of the gender pension gap. All chapters underline the importance of a stable employment biography of women as a way to minimize gender differences in old-age income.

However, Chapter 4 shows that not any form of employment will be beneficial in closing the gap - the mini-job, often chosen by women, is not only damaging to an individual's income security at an old age but its impact is large enough to have a society-wide negative effect that manifests itself in keeping the gender pension gap open. Therefore, Chapter 4 provides an additional argument against mini-jobs and shows that favoring a regular employment can be beneficial on both the individual as well as the society-wide level.

Chapter 4 only discusses one specific scenario - the replacement of a mini-job with a part-time employment. Certainly, other scenarios, like, for example, the choice of full-time work instead of mini-jobs, could be regarded. On the other hand, full-time work seems to be a too different choice to be viable alternative to a mini-job. For sure, the chosen scenario is not one that can be achieved by simple legislative changes - changes in preferences as well as the necessary prerequisites (for example with respect to the availability of care for children or elderly relatives) are needed to allow spending more time in an employment. The scenario can insofar be understood as the maximum that could potentially be achieved by policy changes if these changes also affect preferences and all further requirements are met. Alternatively, a scenario could be examined in which changes in the mini-jobs are not introduced in the present but are assumed to have altered the entire past. This would provide the size of the overall effect of mini-jobs on the gender pension gap. This scenario, however, seems to be far less relevant from the practical perspective, while the chosen one is much more feasible even though its implementation would not be easy. The estimated effect of the scenario on the gender pension gap also has further implications: a more politically feasible legislative change, like a duty to pay pension insurance that cannot be exempted, would certainly have only a minor effect on the pension gap.

While the model in its current form is able to distinguish between different forms of employment, it does, at the moment, only include the general state 'not employed'. This means that the transitions from and to an average type of interruption are discussed. Here, extensions of the simulation model are certainly possible. The reasons for career interruptions, particularly of women, are manifold and might be related to various causes ranging from traditional family patterns (see Blau and Kahn (2007)) over the care for children (see Haan and Wrohlich (2011)) or elderly relatives (see Spieß and Schneider (2003) or Viitanen (2005)) to actual unemployment. The chances to end an unemployment (or any other type of interruption) will, in turn, depend on past career interruption as employment experience will increase the chances of finding a new job. This leads to a further enrichment of the state space and to a more complex model in which one distinguishes between different types of 'not employed' - that being the states 'unemployed', 'child-care', 'informal care', and 'homemaker' - are introduced. This further distinction will provide new insights in the disparities of the long-term effects of different types of interruptions. One might, for instance, suspect that unemployment will also have stronger negative effects with respect to the entire employment life than phases of child care (see also Beblo and Wolf (2002) or Theunissen et al. (2011)). However, as the quantity of transition equations that has to be estimated increases quadratically in the number of states, the number of observations in each estimation declines, and the uncertainty of the estimation results will rise. Therefore, the inclusion of the aggregate state 'not employed' seems to be a reasonable choice - albeit, not necessarily the final expansion stage of the model.

A test of the simulation models could be carried out by building a new simulation model based on older data which is used to predict employment biographies until the current date. In order to evaluate the functionality of the micro-simulation model, the predictions for the current period can be compared with the actual data. Due to its long panel, the SOEP is very well suited to carry out such a test. But generally, one should not expect that different time frames in estimation will substantially alter the results of this study as the predictions are well in line with the current trends.

Various approaches are generally possible to set up a micro-simulation model predicting employment biographies. Chapter 3 discusses some of these possibilities and each way forward will have certain advantages and disadvantages. Among the possible model designs is an approach that directly estimates the number of years that will be spent in certain states (like part or full-time employment) without explicitly determining the sequence of these periods (see Geyer and Steiner (2014)). Another approach completes employment biographies through assigning the subsequent biography of older individuals to that of younger ones by means of statistical matching (see Westermeier et al. (2012)). Certainly, many more concepts are possible. In this work, it was chosen to model employment biographies by an iterative updating based on transition estimations. It thereby provides a newly developed modeling approach for employment biographies and contributes to the empirical literature by offering additional variety with respect to biography simulation techniques. The aforementioned matching approach, for example, will have the disadvantage that future biographies can only evolve in the same manner as biographies of the past due to the assignment of completed employment biographies to younger individuals. In this sense, the matching approach is a retrospective one and lacks opportunities to adapt to recent developments. The model specification chosen in this thesis allows for incorporating much more recent information and is more flexible and dynamic. On the other hand, due the iterative updating, these projected biographies might, as a whole sequence, be farther away from observed biographies than those received from matching. Nevertheless, it has to be noted that within the scope of this thesis not every projected biography has to be necessarily comparable to an observed one - as long as the average projected biography is sensible and realistic. A close inspection of the projected biographies nevertheless reveals that the patterns before and after the start of the prediction are very similar. But ultimately the question on the optimal approach is an empirical one. To come to a conclusion, it is possible to build several of the suggested models based on the same data and estimation equations. Before the start of any prediction process, criteria for the closeness between projection and observed data have to be defined. The testing itself can be carried out by using one part of a panel data-set for prediction and another for validation in a similar manner as described in the previous paragraph.[1]

The choice of the right data-set entails decisions similar to the one on a modeling approach: There is a variety of data-sets providing information on employment in Germany, but only few satisfy most of the essential criteria and none can be deemed to be optimal in all respects. For the decomposition analysis of Chapter 2, just one data-set is needed and the survey *Alterssicherung in Deutschland* (ASID) was chosen. The ASID provides a sufficiently large number of observations, details on pension income, as well as a rich variety of information on socio-economic characteristics. As an alternative, the German Pension Insurance provides data-sets on those receiving pensions under a statutory insurance plan. While this data-set is even larger than the ASID, it provides substantially less information on personal characteristics. This lead to the choice of the ASID. With respect to the micro-simulation models of Chapters 3 and 4, the data situation is more complex. The model requires panel data to trace biographies and to avoid potential endogeneity issues in estimation (see Wooldridge (2010)). Furthermore, detailed information on socio-economic characteristics as well as a sufficiently large number of observations are needed. This necessity of panel data excludes some large and important data-sets like the German micro-census (see Schimpl-Neimanns and Herwig (2011)). Basically, only two candidates for the building up of the micro-simulation model remain: the biography data of the Institute for Employment Research[2] (IAB) and the Socio-Economic panel (SOEP). The IAB is able to provide official data and a substantial number of observations (two percent of the underlying population) with detailed information about their employment biographies up to the current date. It therefore possible to at least approximately calculate the number of earning points these individuals have accumulated in their entire life. For this reason, uncertainty due to the matching of two data-sets can be avoided (see Rässler (2002)). The main advantages of the SOEP and the reasons to be chosen - despite the need for matching SOEP and VKST - are its true panel nature, the rich variety of information on the respondents, and the fact the SOEP covers the entire population and not just those with contributions to the statutory pension scheme. It has to be noted that the SOEP is not without problems itself - most notably, when longer panels are needed the SOEP can suffer from panel attrition (see Spieß and Kroh (2008)), significantly reducing the number of individuals in the data-set.

Other approaches for the simulation of employment biographies can be used. One might, for example, create an extended sample after each iteration by splitting the weights in accordance with the transition probabilities between states. A comparison between the two approaches - extending

[1]See, for example, Hastie et al. (2001) for a discussion on model validation (in the context of statistical learning).
[2]See Oberschachtsiek et al. (2009).

the sample after each iteration and repeatedly predicting for the same population and averaging the results - would certainly be of interest. Extending the state space will, however, come up against its borders when the sample and the number of possible states gets larger as this method will lead to an exponentially increasing sample size.

Bibliography

Adda, J., C. Dustmann, and K. Stevens (2017). 'The career costs of children'. *Journal of Political Economy 125*(2), 293–337.

Allison, P. D. (1978). 'Measures of inequality'. *American Sociological Review 43*(6), 865–880.

Allison, P. D. (2002). 'Missing data: Quantitative applications in the social sciences'. *British Journal of Mathematical and Statistical Psychology 55*(1), 193–196.

Arulampalam, W., A. L. Booth, and M. L. Bryan (2007). 'Is There a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wage Distribution'. *Industrial and Labor Relations Review 60*(2), 163–186.

Atkinson, A. B. (1970). 'On the measurement of inequality'. *Journal of economic theory 2*(3), 244–263.

Bachem, A. and B. Korte (1979, June). 'On the RAS-algorithm'. *Computing 23*(2), 189–198.

Baltagi, B. (2008). *'Econometric analysis of panel data'.* John Wiley & Sons.

Bardasi, E. and S. P. Jenkins (2010). 'The Gender Gap In Private Pensions'. *Bulletin of Economic Research 62*(4), 343–363.

Bargain, O., M. Caliendo, P. Haan, and K. Orsini (2010, January). ''Making work pay' in a rationed labor market'. *Journal of Population Economics 23*(1), 323–351.

Bauer, T. K. and M. Sinning (2008). 'An extension of the Blinder–Oaxaca decomposition to nonlinear models'. *AStA Advances in Statistical Analysis 92*(2), 197–206.

Bauernschuster, S. and M. Schlotter (2015). 'Public child care and mothers' labor supply - Evidence from two quasi-experiments'. *Journal of Public Economics 123*, 1–16.

Beblo, M. and E. Wolf (2002). ‘Wage Penalties for Career Interruptions: An Empirical Analysis for West Germany’. ZEW Discussion Papers 02-45, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

Becker, G. S. (1964). *‘Human capital: a theoretical and empirical analysis, with special reference to education’.* National bureau of economic research publications: General series. National Bureau of Economic Research; distributed by Columbia University Press.

Bender, S., A. Haas, and C. Klose (2000). ‘IAB employment subsample 1975-1995: opportunities for analysis provided by the anonymised subsample’. Technical report, Institut für Arbeitsmarkt- und Berufsforschung (IAB).

Bettio, F. (2017, 12). *‘Can We Call It a Revolution? Women, the Labour Market, and European Policy’*, pp. 15–39. Diana Auth, Jutta Hergenhan, and Barbara Holland-Cunz.

Bettio, F., P. Tinios, and G. Betti (2013). *‘The Gender Gap in Pensions in the EU’.* European Commission.

Bildungsberichterstattung, A. (2012). ‘Bildung in Deutschland 2012. Ein indikatorengestützter Bericht mit einer Analyse zur kulturellen Bildung im Lebenslauf.’. Technical report, Deutsches Institut fÃ¼r Internationale Pädagogische Forschung (DIPF).

Blau, F. D. and L. M. Kahn (1996). ‘Wage Structure and Gender Earnings Differentials: An International Comparison’. *Economica 63*(250), 29–62.

Blau, F. D. and L. M. Kahn (2003). ‘Understanding International Differences in the Gender Pay Gap’. *Journal of Labor Economics 21*(1), 106–144.

Blau, F. D. and L. M. Kahn (2007). ‘Changes in the labor supply behavior of married women: 1980–2000’. *Journal of Labor Economics 25*(3), 393–438.

Blau, F. D. and L. M. Kahn (2016, January). ‘The Gender Wage Gap: Extent, Trends, and Explanations’. Working Paper 21913, National Bureau of Economic Research.

Blinder, A. S. (1973). ‘Wage Discrimination: Reduced Form and Structural Estimates’. *Journal of Human Resources 8*(4), 436–455.

Boersch-Supan, A. and C. B. Wilke (2004). ‘The German Public Pension System: How it Was, How it Will Be’. NBER Working Papers 10525, National Bureau of Economic Research, Inc.

Boll, C. (2011a). 'Lohneinbußen von Frauen durch geburtsbedingte Erwerbsunterbrechungen: Der Schattenpreis von Kindern und dessen mögliche Auswirkungen auf weibliche Spezialisierungsentscheidungen im Haushaltszusammenhang; eine quantitative Analyse auf Basis von SOEP-Daten'. Zugl.: Kiel, Univ., Diss., 2010.

Boll, C. (2011b). 'Mind the gap - German motherhood risks in figures and game theory issues'. *International Economics and Economic Policy 8*(4), 363–382.

Boll, C. and M. Beblo (2014). 'Ökonomische Analysen des Paarverhaltens aus der Lebensverlaufsperspektive und politische Implikationen'. *Vierteljahrshefte zur Wirtschaftsforschung / Quarterly Journal of Economic Research 83*(1), 121–144.

Boll, C., M. Jahn, and A. Lagemann (2017). 'The gender lifetime earnings gap: Exploring gendered pay from the life course perspective'. Technical report, HWWI Research Paper.

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, and S. Zuber (2013). 'Data resource profile: the Survey of Health, Ageing and Retirement in Europe (SHARE)'. *International journal of epidemiology 42*(4), 992–1001.

Börsch-Supan, A., T. Bucher-Koenen, M. Coppola, and B. Lamla (2015). 'Savings in times of demographic change: Lessons from the German experience'. *Journal of Economic Surveys 29*(4), 807–829.

Börsch-Supan, A., T. Bucher-Koenen, and J. Rausch (2016). 'Szenarien für eine nachhaltige Finanzierung der Gesetzlichen Rentenversicherung/Scenarios for the Sustainable Financing of the State Pension System'. *ifo Schnelldienst 69*(18), 31.

Börsch-Supan, A. and C. B. Wilke (2004). 'The German public pension system: how it was, how it will be'. Technical report, National Bureau of Economic Research.

Bourguignon, F. (1979). 'Decomposable income inequality measures'. *Econometrica 47*(4), 901–920.

Brady, D. and T. Biegert (2017). 'The Rise of Precarious Employment in Germany'. LIS Working papers 708, LIS Cross-National Data Center in Luxembourg.

Büchel, F. and C. K. Spieß (2002). 'Kindertageseinrichtungen und Müttererwerbstätigkeit: neue Erkenntnisse zu einem bekannten Zusammenhang'. *Vierteljahrshefte zur Wirtschaftsforschung / Quarterly Journal of Economic Research 71*(1), 95–113.

Buis, M. L. (2010, May). 'ZOIB: Stata module to fit a zero-one inflated beta distribution by maximum likelihood'. Statistical Software Components, Boston College Department of Economics.

Champernowne, D. G. and F. A. Cowell (1998). *'Economic inequality and income distribution'*. Cambridge University Press.

Chetty, R., M. Stepner, and S. Abraham (2016). 'The association between income and life expectancy in the united states, 2001-2014'. *JAMA 315*(16), 1750–1766.

Ciani, E. (2012). 'Informal adult care and caregivers' employment in Europe'. *Labour Economics 19*(2), 155 – 164.

Cotton, J. (1988). 'On the Decomposition of Wage Differentials'. *The Review of Economics and Statistics 70*(2), 236–43.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996). 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach'. *Econometrica 64*(5), 1001–44.

D'Orazio, M., M. Di Zio, and M. Scanu (2006). *'Statistical Matching: Theory and Practice'*. Wiley Series in Survey Methodology. Wiley.

Drobnič, S., H.-P. Blossfeld, and G. Rohwer (1999). 'Dynamics of women's employment patterns over the family life course: A comparison of the United States and Germany'. *Journal of Marriage and the Family 61*(1), 133–146.

Drosdowski, T., C. Hänisch, M. Kalinowski, A. Mönning, B. Stöver, P. Ulrich, and M. I. Wolter (2017). *'Gesamtwirtschaftliche Entwicklung 1991 bis 2030'*. Forschungsverbund Sozioökonomische Berichterstattung (SOEB).

Ejrnaes, M. and A. Kunze (2013). 'Work and Wage Dynamics Around Childbirth'. *The Scandinavian Journal of Economics 115*(3), 856–877.

Even, W. E. and D. A. Macpherson (2004). 'When Will the Gender Gap in Retirement Income Narrow?'. *Southern Economic Journal 71*(1), 182–200.

Faik, J. and T. Köhler-Rama (2012, May). 'Der Gender Pension Gap - Ungeeigneter Indikator'. *Wirtschaftsdienst 92*(5), 319–325.

Favreault, M. and K. Smith (2004). 'A Primer on the Dynamic Simulation of Income Model'. Discussion Paper 02-22, Urban Institute.

Firpo, S., N. Fortin, and T. Lemieux (2007). 'Decomposing wage distributions using recentered influence function regressions'. Technical report, University of British Columbia (June).

Firpo, S., N. M. Fortin, and T. Lemieux (2009). 'Unconditional Quantile Regressions'. *Econometrica 77*(3), 953–973.

Fitzenberger, B. and A. Kunze (2005). 'Vocational Training and Gender: Wages and Occupational Mobility among Young Workers'. *Oxford Review of Economic Policy 21*(3), 392–415.

Flory, J. (2011). 'Gender Pension Gap - Entwicklung eines Indikators für faire Einkommensperspektiven von Frauen und Männern'. Technical report, Bundesministerium für Familie, Senioren, Frauen und Jugend, Berlin.

Flory, J. and S. Stöwhase (2012). 'MIKMOD-ESt: A static microsimulation model of personal income taxation in Germany'. *International Journal of Microsimulation 5*(2), 66–73.

Fortin, N., T. Lemieux, and S. Firpo (2011). *'Decomposition Methods in Economics'*, Volume 4 of *Handbook of Labor Economics*, Chapter 1, pp. 1–102. Elsevier.

Franz, N. (2011). *'Geschlechtsspezifische Verdienstunterschiede und Diskriminierung am Arbeitsmarkt: eine Untersuchung unter Berücksichtigung von Voll- und Teilzeitarbeit'.* Diskussionspapier. CIW.

Frick, J. R. and K. Krell (2011). 'Einkommensmessungen in Haushaltspanelstudien für Deutschland: ein Vergleich von EU-SILC und SOEP'. *AStA Wirtschafts-und Sozialstatistisches Archiv 5*(3), 221–248.

Frommert, D. and S. Strauß (2013). 'Biografische Einflussfaktoren auf den Gender Pension Gap : Ein Kohortenvergleich für Westdeutschland'. *Journal for Labour Market Research 46*(2), 145–166.

Galassi, G. (2017). 'The German Mini-Job Reform: Intended and Unintended Consequences'. Technical report, European University Institute.

Gangl, M. and A. Ziefle (2009). 'Motherhood, labor force behavior, and women's careers: An empirical assessment of the wage penalty for motherhood in Britain, Germany, and the United States'. *Demography 46*(2), 341–369.

Geyer, J. (2011). 'Riester-Rente: Rezept gegen Altersarmut?'. *DIW Wochenbericht 78*(47), 16–21.

Geyer, J. and V. Steiner (2014). 'Future public pensions and changing employment patterns across birth cohorts'. *Journal of Pension Economics and Finance 13*(2), 172–209.

Gini, C. (1921). 'Measurement of inequality of incomes'. *The Economic Journal 31*(121), 124–126.

Goebel, J. and M. M. Grabka (2011). 'Entwicklung der Altersarmut in Deutschland'. *Vierteljahrshefte zur Wirtschaftsforschung 80*(2), 101–118.

Grabka, M. M., B. Jotzo, A. Rasner, and C. Westermeier (2017). 'Der Gender Pension Gap verstärkt die Einkommensungleichheit von Männern und Frauen im Rentenalter'. *DIW-Wochenbericht 84*(5), 87–96.

Greene, W. H. (2003). *Econometric Analysis* (5. ed.). Upper Saddle River, NJ: Prentice Hall.

Gupta, A. and V. Kapur (2000). *'Microsimulation in Government Policy and Forecasting'.* Contributions to economic analysis. Elsevier.

Gupta, N. and N. Smith (2002). 'Children and Career Interruptions: The Family Gap in Denmark'. *Economica 69*(276), 609–629.

Gutierrez-Domenech, M. (2004, 08). 'Employment After Motherhood: A European Comparison'. *Labour Economics 12*, 99–123.

Haan, P., A. Hammerschmid, and C. Rowold (2017). 'Gender gaps in pensions and health: Germany, France, and Denmark'. *DIW Economic Bulletin 43*, 436 – 442.

Haan, P. and V. Prowse (2014). 'Longevity, life-cycle behavior and pension reform'. *Journal of Econometrics 178*, 582–601.

Haan, P. and V. L. Prowse (2015). 'Optimal social assistance and unemployment insurance in a life-cycle model of family labor supply and savings'. Diw berlin discussion paper, Deutsches Institut für Wirtschaftsforschung (DIW).

Haan, P., H. Stichnoth, M. Blömer, H. Buslei, J. Geyer, C. Krolage, and K.-U. Müller (2017). 'Entwicklung der Altersarmut bis 2036: Trends, Risikogruppen und Politikszenarien'. Zew-gutachten und forschungsberichte, ZEW, Gütersloh.

Haan, P. and K. Wrohlich (2011). 'Can child care policy encourage employment and fertility?: Evidence from a structural model'. *Labour Economics 18*(4), 498 – 512.

Hamilton, J. (1994). *'Time Series Analysis'.* Princeton University Press.

Hänisch, C. and J. Klos (2014). 'A Decomposition Analysis of the German Gender Pension Gap'. Technical report, Fraunhofer FIT.

Hastie, T., R. Tibshirani, and J. Friedman (2001). *'The Elements of Statistical Learning'.* Springer Series in Statistics. New York, NY, USA: Springer New York Inc.

Heckman, J. J. (1977). Sample selection bias as a specification error (with an application to the estimation of labor supply functions).

Heckman, J. J. (1979). 'Sample Selection Bias as a Specification Error'. *Econometrica 47*(1), 153–61.

Heien, T., K. Kortmann, and C. Schatz (2005). 'Altersvorsorge in Deutschland 2005'. Technical report, Deutsche Rentenversicherung.

Heinze, A. (2010). 'Beyond the mean gender wage gap: Decomposition of differences in wage distributions using quantile regression'. ZEW Discussion Papers 10-043, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

Herriot, R. A. and D. Kasprzyk (1984). Survey of income and program participation. Technical report, Washington DCUS Bureau of the Census 1984.

Huebener, M., K.-U. Müller, C. K. Spieß, and K. Wrohlich (2016). 'Zehn Jahre Elterngeld: Eine wichtige familienpolitische Maßnahme'. *DIW-Wochenbericht 83*(49), 1159–1166.

Iacus, S. M., G. King, and G. Porro (2012, December). 'Causal Inference without Balance Checking: Coarsened Exact Matching'. *Political Analysis 20*(01), 1–24.

Jann, B. (2008). 'The Blinder-Oaxaca decomposition for linear regression models'. *Stata Journal 8*(4), 453–479(27).

Johnson, R. W. (1999). 'The Gender Gap in Pension Wealth. Is Women's Progress in the Labor Market Equalizing Retirement Benefits?'. The retirement project, brief series no. 1, Urban Institute, Washington, DC.

Juhn, C., K. M. Murphy, and B. Pierce (1993). 'Wage Inequality and the Rise in Returns to Skill'. *Journal of Political Economy 101*(3), 410–42.

Klenner, C. and T. Schmidt (2011). 'Teilzeitarbeit im Lebensverlauf von abhängig beschäftigten Frauen'. In *Neue Wege–Gleiche Chancen*, pp. 253–311. Springer.

Kolmar, M. (2007). 'Beveridge versus Bismarck public-pension systems in integrated markets'. *Regional Science and Urban Economics 37*(6), 649–669.

Körner, T., H. Meinken, and K. Puch (2013). 'Wer sind die ausschließlich geringfügig Beschäftigten? Eine Analyse nach sozialer Lebenslage.'. Wirtschaft und Statistik H. 1, S. 42-61, Bundesministerium fr̈ Arbeit und Soziales, Berlin.

Kortmann, K. and V. Halbherr (2008). 'Alterssicherung in Deutschland 2007 (ASID '07) - Zusammenfassung wichtiger Untersuchungsergebnisse'. BMAS Forschungsbericht 391/Z, Bundesministerium fr̈ Arbeit und Soziales, Berlin.

Kortmann, K. and J. Heckmann (2012). 'Alterssicherung in Deutschland 2011. Zusammenfassender Bericht'.

Kreyenfeld, M. (2009). 'Uncertainties in female employment careers and the postponement of parenthood in Germany'. *European Sociological Review 26*(3), 351–366.

Kreyenfeld, M. and K. Hank (2000). 'Does the availability of child care influence the employment of mothers? Findings from western Germany'. *Population Research and Policy Review 19*(4), 317–337.

Kunze, A. et al. (2017). 'The Gender Wage Gap in Developed Countries'. Technical report, Institute for the Study of Labor (IZA).

Lemieux, T. (2006). *'The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings'.* Working paper (University of California, Berkeley. Center for Labor Economics). Center for Labor Economics, University of California, Berkeley.

Levine, P. B., O. S. Mitchell, and J. W. Phillips (1999). 'Worklife Determinants of Retirement Income Differentials Between Men and Women'. Pension Research Council Working Papers 99-19, Wharton School Pension Research Council, University of Pennsylvania.

Li, J., C. O'Donoghue, J. Loughrey, and A. Harding (2014). 'Static Models'. In *Handbook of Microsimulation Modelling*, Volume 293, pp. 47–75. Emerald Publishing Ltd.

Licht, G. and V. Steiner (1992). 'Individuelle Einkommensdynamik und Humankapitaleffekte nach Erwerbsunterbrechung'. *Jahrbuch für Nationalökonomie und Statistik 209*(2-3), 241–265.

Light, A. and M. Ureta (1995). 'Early Career Work Experience and Gender Wage Differentials'. *Journal of Labor Economics 13*(1), 121–154.

Marimont, R. B. and M. B. Shapiro (1979). 'Nearest Neighbour Searches and the Curse of Dimensionality'. *IMA Journal of Applied Mathematics 24*(1), 59–70.

Mata, J. and J. A. F. Machado (2005). 'Counterfactual decomposition of changes in wage distributions using quantile regression'. *Journal of Applied Econometrics 20*(4), 445–465.

Merz, J. (1991). 'Microsimulation - A survey of principles, developments and applications'. *International Journal of Forecasting 7*(1), 77 – 104.

Merz, J. (1994, June). 'Microsimulation - A Survey of Methods and Applications for Analyzing Economic and Social Policy'. FFB-Discussionpaper 09, Research Institute on Professions (Forschungsinstitut Freie Berufe (FFB)), LEUPHANA University Lüneburg.

Michalopoulos, C., P. K. Robins, and I. Garfinkel (1992). 'A structural model of labor supply and child care demand'. *Journal of Human Resources 27*(1), 166–203.

Michaud, P. and S. Rohwedder (2008). 'Forecasting Labor Force Participation and Economic Resources of the Early Baby Boomers'. Discussion Paper 02-33, Retirement Research Center, Michigan (MRRC).

Michaud, P.-C., A. Heitmueller, and Z. Nazarov (2010). 'A dynamic analysis of informal care and employment in England'. *Labour Economics 17*(3), 455 – 465.

Mika, T. (2017). 'Different Employment Pathways into the Pension for Reduced Earnings Capacity'. *Sozialer Fortschritt 66*(1), 31–47.

Mincer, J. and H. Ofek (1982). 'Interrupted Work Careers: Depreciation and Restoration of Human Capital'. *Journal of Human Resources 17*(1), 3–24.

Mincer, J. and S. Polachek (1974a). 'Family Investments in Human Capital: Earnings of Women'. *Journal of Political Economy 82*(2), 76–108.

Mincer, J. and S. Polachek (1974b). Family investments in human capital: Earnings of women. *Journal of political Economy 82*(2, Part 2), S76–S108.

Mincer, J. A. (1974). *'Schooling, Experience, and Earnings'.* Number minc74-1 in NBER Books. National Bureau of Economic Research, Inc.

Minijobzentrale (2017). '2. Quartalsbericht 2017'. Technical report, Minijobzentrale.

Neumark, D. (1988). 'Employers' Discriminatory Behavior and the Estimation of Wage Discrimination'. *Journal of Human Resources 23*(3), 279–295.

Oaxaca, R. (1973). 'Male-Female Wage Differentials in Urban Labor Markets'. *International Economic Review 14*(3), 693–709.

Oaxaca, R. L. and M. R. Ransom (1994). 'On discrimination and the decomposition of wage differentials'. *Journal of Econometrics 61*(1), 5–21.

Oberschachtsiek, D., P. Scioch, C. Seysen, J. Heining, et al. (2009). 'Stichprobe der Integrierten Erwerbsbiografien'. Technical report, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].

O'Donoghue, C. (2001, December). 'Dynamic Microsimulation: A Methodological Survey'. *Brazilian Electronic Journal of Economics 4*(2), 1 – 77.

O'Donoghue, C., J. Lennon, and S. Hynes (2009). 'The Life-Cycle Income Analysis Model (LIAM): A Study of a Flexible Dynamic Microsimulation Modelling Computing Framework'. *International Journal of Microsimulation 2*(1), 16–31.

Orcutt, G. H., J. Merz, and H. Quinke (1986). *'Microanalytic simulation models to support social and financial policy'.* North-Holland.

O'Reilly, J., M. Smith, S. Deakin, and B. Burchell (2015). 'Equal pay as a moving target: International perspectives on forty-years of addressing the gender pay gap'. *Cambridge Journal of Economics 39*(2), 299–317.

Ospina, R. and S. L. Ferrari (2012). 'A general class of zero-or-one inflated beta regression models'. *Computational Statistics and Data Analysis 56*(6), 1609 – 1623.

Plantenga, J. and C. Remery (2006). 'The Gender Pay Gap: Origins and Policy Responses. A Comparative Review of Thirty European Countries'. Technical report, Group Of Experts On Gender, Social Inclusion And Employment, Luxembourg, Office for Official Publications of the European Communities.

Potrafke, N. (2007). 'The timing of employment breaks: how does it affect pension benefits? Empirical evidence from Germany'. Discussion Paper 02-30, Deutsches Institut für Wirtschaftsforschung (DIW).

Pötzsch, O. (2017). 'Demografisches Bild der Fertilität in Deutschland vor und nach dem Zensus 2011: Noch keine Trendwende in Sicht'. *Comparative Population Studies-Zeitschrift für Bevölkerungswissenschaft 41*, 67–100.

Rasner, A. (2014). 'Gender Pension Gap in Eastern and Western Germany'. DIW Economic Bulletin 11/14, DIW - Deutsches Institut für Wirtschaftsforschung / German Institute for Economic Research.

Rässler, S. (2002). *'Statistical Matching: A Frequentist Theory, Practical Applications, and Alternative Bayesian Approaches'.* Lecture Notes in Statistics. Springer New York.

Rentenversicherung, D. (2017). 'Rentenversicherung in Zahlen 2017'. Technical report, Deutsche Rentenversicherung.

Rosenbaum, P. R. and D. B. Rubin (1983). 'The central role of the propensity score in observational studies for causal effects'. *Biometrika 70*(1), 41–55.

Rubin, D. B. (1973). 'Matching to Remove Bias in Observational Studies'. *Biometrics 29*(1), 159–183.

Rubin, D. B. (1987). *'Multiple Imputation for Nonresponse in Surveys'.* Wiley.

Rürup, B. (2002). 'The German pension system: status Quo and Reform options'. In *Social security pension reform in Europe*, pp. 137–170. University of Chicago Press.

Scheele, A. (2013). 'Frauenerwerbstätigkeit im Spannungsfeld von Prekarisierung und guter Arbeit -Geschlechterpolitische Erweiterungen/Women's employment between the opposing poles of precarious work and job quality. Revisions from a gender equality perspective'. *Arbeit 22*(3), 187–198.

Schimpl-Neimanns, B. and A. Herwig (2011). *'Mikrozensus Scientific Use File 2011: Dokumentation und Datenaufbereitung'*, Volume 2011/11. GESIS - Leibniz-Institut für Sozialwissenschaften in Mannheim.

Schludi, M. (2010). *'The reform of Bismarckian pension systems: a comparison of pension politics in Austria, France, Germany, Italy and Sweden'*. Amsterdam University Press.

Shorrocks, A. F. (1980). 'The class of additively decomposable inequality measures'. *Econometrica: Journal of the Econometric Society 48*(3), 613–625.

Simonson, J., N. Kelle, L. R. Gordo, M. M. Grabka, A. Rasner, and C. Westermeier (2012). 'Ostdeutsche Männer um 50 müssen mit geringeren Renten rechnen'. *DIW-Wochenbericht 79*(23), 3–13.

Söhn, J. and T. Mika (2017, 03). 'Wie das Rentensystem Erwerbsbiografien würdigt'.

Spieß, C. K. and A. U. Schneider (2003). 'Interactions between care-giving and paid work hours among European midlife women, 1994 to 1996'. *Ageing & Society 23*(1), 41–68.

Spieß, M. and M. Kroh (2008). 'Documentation of sample sizes and panel attrition in the German Socio Economic Panel (SOEP)(1984 until 2006)'. Technical report, Data Documentation.

Spivey, C. (2005). 'Time off at What Price? The Effects of Career Interruptions on Earnings'. *Industrial & Labor Relations Review 59*(1), 119–140.

Statistisches Bundesamt (2012). 'Bevölkerung und Erwerbstätigkeit Stand und Entwicklung der Erwerbstätigkeit in Deutschland'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2014). 'Verdienststrukturerhebung - Ergebnisse für Deutschland - Fachserie 16 Heft 1'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2015). 'Bevölkerung Deutschlands bis 2060 - 13. koordinierte Bevölkerungsvorausberechnung'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2016a). 'Bevölkerung mit Migrationshintergrund - Ergebnisse des Mikrozensus'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2016b). 'Bevölkerung und Erwerbstätigkeit Stand und Entwicklung der Erwerbstätigkeit in Deutschland'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2016c). 'Bevölkerung und Erwerbstätigkeit Stand und Entwicklung der Erwerbstätigkeit in Deutschland'. Technical report, Statistisches Bundesamt, Wiesbaden.

Statistisches Bundesamt (2017). 'Kohortensterbetafeln für Deutschland - Ergebnisse aus den Modellrechnungen für Sterbetafeln nach Geburtsjahrgang'. Technical report, Statistisches Bundesamt, Wiesbaden.

Steiner, V. and K. Wrohlich (2005a). 'Minijob-Reform: Keine durchschlagende Wirkung'. *DIW Wochenbericht 72*(8), 141–146.

Steiner, V. and K. Wrohlich (2005b). 'Work incentives and labor supply effects of the 'Mini-jobs reform' in Germany'. *Empirica 32*(1), 91–116.

Sutherland, H., H. Immervoll, and C. O'Donoghue (1999, September). 'An introduction to EUROMOD'. EUROMOD Working Papers EM0/99, EUROMOD at the Institute for Social and Economic Research.

Tazhitdinova, A. (2017). 'Adjust Me if I Can't: The Effect of Firm Incentives on Labor Supply Responses to Taxes'. MPRA Paper 81611, University Library of Munich, Germany.

Theunissen, G., M. Verbruggen, A. Forrier, and L. Sels (2011). 'Career sidestep, wage setback? The impact of different types of employment interruptions on wages'. *Gender, Work & Organization 18*(s1), 110 – 131.

Unterhofer, U., C. Welteke, and K. Wrohlich (2017). 'Elterngeld hat soziale Normen verändert'. *DIW-Wochenbericht 84*(34), 659–667.

Viitanen, T. K. (2005). 'Informal Elderly Care and Women's Labour Force Participation across Europe'. ENEPRI Research Report 13, ENEPRI.

Wagner, G., J. Frick, and J. Schupp (2007). 'The German Socio-Economic Panel Study (SOEP) Scope, Evolution and Enhancements'. *Schmollers Jahrbuch 127*(1), 139–169.

Wagner, G. G., J. Schupp, and U. Rendtel (1991). 'The Socio-Economic Panel (SOEP) for Germany: Methods of production and management of longitudinal data'. Technical report, DIW Discussion Papers.

Weichselbaumer, D. and R. Winter-Ebmer (2005). 'A Meta-Analysis of the International Gender Wage Gap'. *Journal of Economic Surveys 19*(3), 479–511.

Weinkopf, C. (2009). Germany: precarious employment and the rise of mini-jobs.

Westermeier, C., M. M. Grabka, B. Jotzo, and A. Rasner (2017). 'Veränderung der Erwerbs- und Familienbiografien lässt einen Rückgang des Gender-Pension-Gap erwarten'. *DIW Wochenbericht 84*(12), 235–243.

Westermeier, C., A. Rasner, and M. Grabka (2012). 'The prospects of the Baby Boomers: Methodological challenges in projecting the lives of an aging cohort'. Discussion Paper 02-58, Deutsches Institut für Wirtschaftsforschung (DIW).

Willis, R. J. (1986). 'Wage determinants: A survey and reinterpretation of human capital earnings functions'. *Handbook of labor economics 1*, 525–602.

Wooldridge, J. M. (2010). *'Econometric analysis of cross section and panel data'.* MIT press.

Wrohlich, K. and A. Zucco (2017). 'Gender Pay Gap innerhalb von Berufen variiert erheblich'. *DIW Wochenbericht 84*(43), 955–961.

Zika, G., R. Helmrich, M. Kalinowski, M. I. Wolter, M. Hummel, T. Maier, C. Hänisch, and T. Drosdowski (2012). 'Qualifikations- und Berufsfeldprojektionen bis 2030: In der Arbeitszeit steckt noch eine Menge Potenzial'. IAB-Kurzbericht 18/2012, Institut für Arbeitsmarkt- und Berufsforschung (IAB).

Appendix A

A Decomposition Analysis of the German Gender Pension Gap

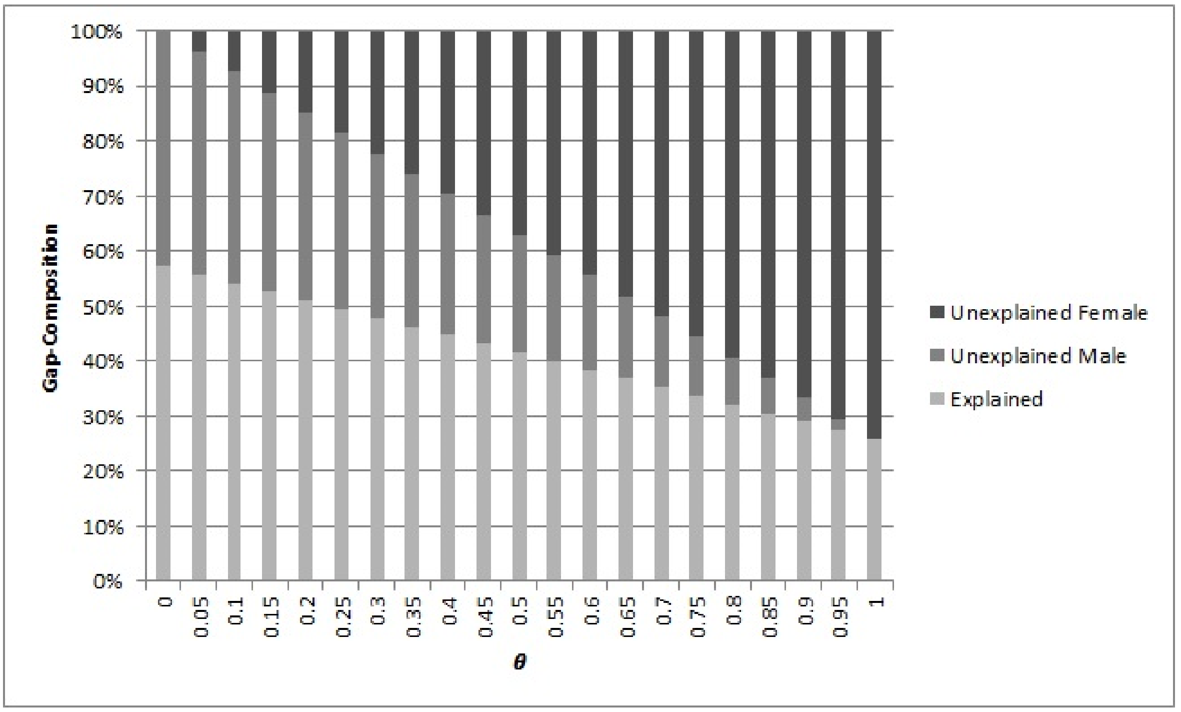
Choice of reference group

Various approaches have been suggested to select an appropriate reference group in the decomposition analysis (see for example Oaxaca (1973), Blinder (1973) or Cotton (1988)). It is well known that these choices are important as they substantially affect the sizes of the gap's explained and unexplained part (as well as each component of the explained and unexplained part). As, especially in the public discussion, 'unexplained' is still sometimes associated with 'discriminatory' and to provide a better intuition of the results, it seems to be important to consider this aspect and it is therefore briefly described how the decomposition results react to changes in the reference group. For this reason, this analysis depicts the gap parts after a decomposition for varying choice of a reference group. At first, the results with reference groups constructed as convex combinations of the male and female coefficient vector ($\beta^* = \theta * \beta^M + (1-\theta) * \beta^F, \theta \in [0,1]$) are shown.

Figure A.1 shows that, depending on the choice of the reference category between β^M and β^F, the size of the gap's explained part lies in an interval of about 30 up to almost 60 percent. These are certainly substantial differences. Another approach is to use the coefficient vector of a pooled regression with both men and women as reference (see Oaxaca and Ransom (1994) or Neumark (1988)). The results are shown in Figure A.2.

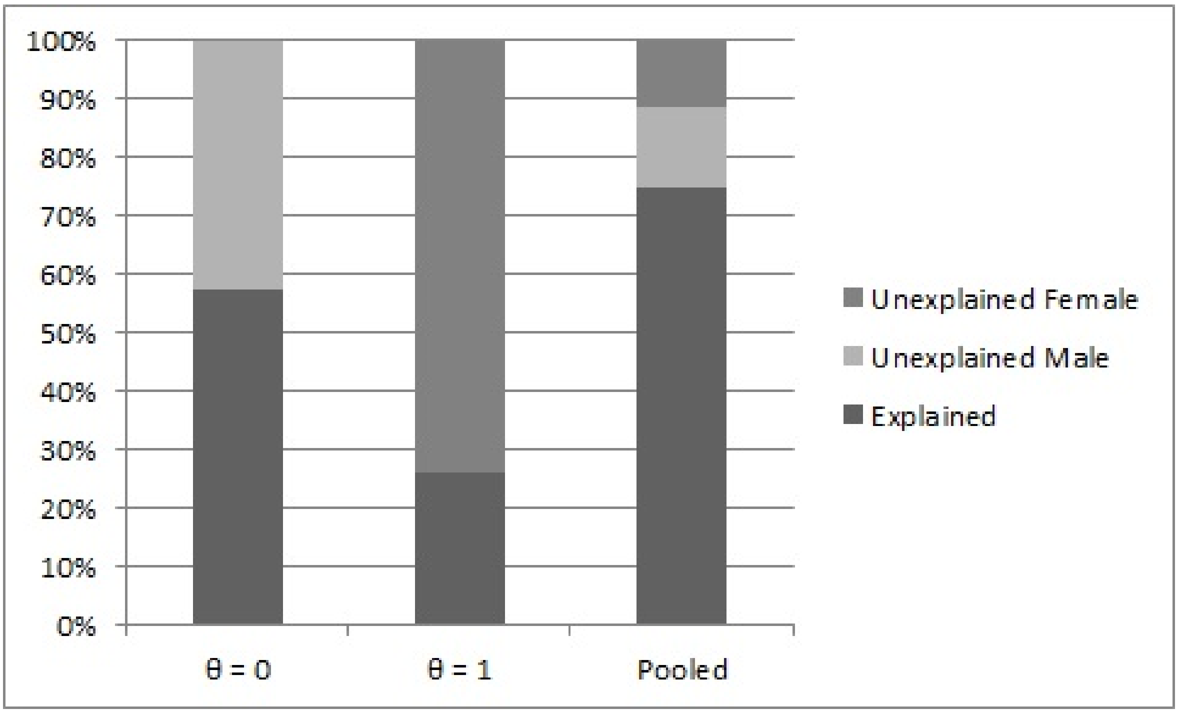
It as apparent that the explained part of the gap has further increased compared to the previous results

Figure A.1
Gap composition for increasing θ



Source: ASID 2007, authors' calculations

Figure A.2
Gap composition for different β^*



Source: ASID 2007, authors' calculations using the pooled regression results as reference[1], underlining the effects of the reference group choice. This certainly shows that the absolute sizes of the parts of the gap should not be over-interpreted and that instead the focus should be laid on those variables contributing the most to the gap.

[1] for further details and potential methodological problems see Jann (2008).

Results of the mean decomposition analysis

Table A.1
Results of Oaxaca-Blinder decomposition of own pension income

	Log Own Pension
	b
overall	
men	7.272***
women	6.226***
difference	1.046***
explained	0.271***
unexplained	0.775***
explained	
Years of Employment: Self-Employed	-0.006***
Years of Employment: Private Industry	0.112***
Years of Employment: Public Service	-0.004
Years of Employment: Civil Service	0.057***
noncontinuous employment-history	0.034
Has Never Been Employed	0.000
Worker	-0.001
Employee	-0.014***
Civil Servant	0.007
Self-Employed	-0.002
No training	0.050***
Vocational Training	-0.004***
Master Craftperson, Polytechnics	0.001
University	0.018***
Miscellaneous Training	-0.000
Married	0.034***
Widowed	-0.025***
Divorced	0.003**
Single	0.001
Children	0.002
Region	0.009***
unexplained	
Years of Employment: Self-Employed	-0.032***
Years of Employment: Private Industry	-0.348***
Years of Employment: Public Service	-0.117***
Years of Employment: Civil Service	-0.012**
noncontinuous employment-history	0.052
Has Never Been Employed	0.001
Worker	-0.011
Employee	0.037
Civil Servant	-0.005
Self-Employed	0.006
No training	0.008
Vocational Training	0.010
Master Craftperson, Polytechnics	-0.003**
University	0.002
Miscellaneous Training	-0.000
Married	0.115***
Widowed	0.115***
Divorced	-0.024***
Single	-0.015***
Children	-0.050***
Region	-0.058***
Constant	1.107***
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.2
Regression results - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.006***
Years of Employment: Private Industry	0.010***
Years of Employment: Public Service	0.012***
Years of Employment: Civil Service	0.021***
noncontinuous employment-history	-0.077
Has Never Been Employed	-0.057
Worker	-0.0901***
Employee	0.127***
Civil Servant	0.100
Self-Employed	-0.080*
No Training	-0.182***
Vocational Training	-0.0916***
Master Craftperson, Polytechnics	0.004
University	0.312***
Miscellaneous Training	-0.043**
Married	0.107***
Widowed	-0.088***
Divorced	-0.156***
Single	-0.038
Children	-0.005
Region	-0.315***
Constant	6.880***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.3
Regression results - women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	0.006**
Years of Employment: Private Industry	0.028***
Years of Employment: Public Service	0.034***
Years of Employment: Civil Service	0.043***
noncontinuous employment-history	-0.188***
Has Never Been Employed	-0.220*
Worker	-0.062
Employee	0.055
Civil Servant	0.394
Self-Employed	-0.166 *
No Training	-0.201***
Vocational Training	-0.112***
Master Craftperson, Polytechnics	0.081***
University	0.268***
Miscellaneous Training	-0.035
Married	-0.151***
Widowed	-0.193***
Divorced	0.165***
Single	0.178***
Children	0.020***
Region	-0.060***
Constant	5.774***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: ASID 2007, authors' estimations

Results of the Quantile Decomposition Analysis

Table A.4
Decomposition for 10 % quantile

	Log Own Pension b
overall	
men	6.718***
women	5.130***
difference	1.588*
explained	0.523***
unexplained	1.065
explained	
Years of Employment: Self-Employed	-0.011*
Years of Employment: Private Industry	0.300***
Years of Employment: Public Service	-0.010***
Years of Employment: Civil Service	0.053***
noncontinuous employment-history	0.078
Has Never Been Employed	-0.0003***
Worker	-0.001*
Employee	0.002
Civil Servant	0.024**
Self-Employed	-0.009**
No training	0.050***
Vocational Training	-0.002
Master Craftperson, Polytechnics	-0.002
University	0.015***
Miscellaneous Training	-0.0001
Married	0.055***
Widowed	-0.039**
Divorced	0.004**
Single	0.002
Children	0.013*
Region	0.004***
unexplained	
Years of Employment: Self-Employed	-0.098***
Years of Employment: Private Industry	-0.268*
Years of Employment: Public Service	-0.055
Years of Employment: Civil Service	-0.008
noncontinuous employment-history	-0.176*
Has Never Been Employed	0.002
Worker	-0.111
Employee	-0.114
Civil Servant	-0.0003
Self-Employed	0.014
No training	0.004
Vocational Training	-0.010
Master Craftperson, Polytechnics	-0.003
University	0.006
Miscellaneous Training	-0.005
Married	0.103***
Widowed	0.103***
Divorced	-0.026***
Single	-0.009
Children	-0.180***
Region	-0.035***
Constant	1.931**
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.5
RIF-regression results at 10 % quantile - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.011*
Years of Employment: Private Industry	0.027***
Years of Employment: Public Service	0.029***
Years of Employment: Civil Service	0.019***
noncontinuous employment-history	-0.177
Has Never Been Employed	0.160***
Worker	-0.136*
Employee	-0.014
Civil Servant	0.324**
Self-Employed	-0.333**
No Training	-0.181***
Vocational Training	-0.046
Master Craftperson, Polytechnics	-0.010
University	0.274***
Miscellaneous Training	-0.037
Married	0.174***
Widowed	0.142**
Divorced	-0.227**
Single	-0.089
Children	-0.028*
Region	-0.130***
Constant	5.766***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.6
RIF-regression results at 10 % quantile- women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	0.026***
Years of Employment: Private Industry	0.041***
Years of Employment: Public Service	0.040***
Years of Employment: Civil Service	0.034**
noncontinuous employment-history	0.199**
Has Never Been Employed	-0.146
Worker	0.141
Employee	0.209
Civil Servant	0.342
Self-Employed	-0.546
No Training	-0.192***
Vocational Training	-0.024
Master Craftperson, Polytechnics	0.056
University	0.114
Miscellaneous Training	0.046
Married	-0.055**
Widowed	-0.110**
Divorced	0.126***
Single	0.040
Children	0.060***
Region	0.208
Constant	3.835***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.7
Decomposition for 25 % quantile

	Log Own Pension
	b
overall	
men	7.022***
women	5.710***
difference	1.312***
explained	0.214***
unexplained	1.098**
explained	
Years of Employment: Self-Employed	-0.004**
Years of Employment: Private Industry	0.117***
Years of Employment: Public Service	-0.005***
Years of Employment: Civil Service	0.023***
noncontinuous employment-history	0.013
Has Never Been Employed	0.0001*
Worker	-0.001
Employee	-0.005
Civil Servant	0.013*
Self-Employed	-0.002
No training	0.034***
Vocational Training	-0.002
Master Craftperson, Polytechnics	0.004
University	0.009***
Miscellaneous Training	-0.00003
Married	0.030***
Widowed	-0.023***
Divorced	0.003***
Single	0.0006
Children	0.004
Region	0.007***
unexplained	
Years of Employment: Self-Employed	-0.060***
Years of Employment: Private Industry	-0.758***
Years of Employment: Public Service	-0.201***
Years of Employment: Civil Service	-0.019**
noncontinuous employment-history	0.057
Has Never Been Employed	0.002**
Worker	-0.046
Employee	-0.077
Civil Servant	-0.004
Self-Employed	0.011
No training	0.017
Vocational Training	0.011
Master Craftperson, Polytechnics	-0.002
University	0.001
Miscellaneous Training	-0.002
Married	0.095***
Widowed	0.116***
Divorced	-0.030***
Single	-0.006*
Children	-0.122***
Region	-0.084***
Constant	2.199***
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.8
RIF-regression results at 25 % quantile - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.004**
Years of Employment: Private Industry	0.011***
Years of Employment: Public Service	0.013***
Years of Employment: Civil Service	0.008***
noncontinuous employment-history	-0.029
Has Never Been Employed	-0.067*
Worker	-0.087
Employee	0.048
Civil Servant	0.174*
Self-Employed	-0.067
No Training	-0.123***
Vocational Training	-0.038
Master Craftperson, Polytechnics	0.022
University	0.156***
Miscellaneous Training	-0.017
Married	0.095***
Widowed	0.083***
Divorced	-0.149***
Single	-0.030
Children	-0.008
Region	-0.255***
Constant	6.644***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: ASID 2007, authors' estimations

Table A.9
RIF-regression results at 25 % quantile - women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	0.018***
Years of Employment: Private Industry	0.050***
Years of Employment: Public Service	0.051***
Years of Employment: Civil Service	0.043***
noncontinuous employment-history	-0.150*
Has Never Been Employed	-0.399**
Worker	0.028
Employee	0.199
Civil Servant	0.402
Self-Employed	-0.230
No Training	-0.166***
Vocational Training	-0.062
Master Craftperson, Polytechnics	0.070
University	0.143*
Miscellaneous Training	0.015
Married	-0.117***
Widowed	-0.202***
Divorced	0.264***
Single	0.055
Children	0.052***
Region	0.120***
Constant	4.445***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.10
Decomposition for 50 % quantile

	Log Own Pension
	b
overall	
men	7.275***
women	6.398***
difference	0.877***
explained	0.161***
unexplained	0.717**
explained	
Years of Employment: Self-Employed	-0.002
Years of Employment: Private Industry	0.087***
Years of Employment: Public Service	-0.004***
Years of Employment: Civil Service	0.029***
noncontinuous employment-history	-0.021
Has Never Been Employed	0.0003**
Worker	-0.001
Employee	-0.012
Civil Servant	0.016
Self-Employed	-0.001
No training	0.040***
Vocational Training	-0.002**
Master Craftperson, Polytechnics	0.005
University	0.009***
Miscellaneous Training	-0.00002
Married	0.026***
Widowed	-0.026***
Divorced	0.002***
Single	0.001
Children	0.004*
Region	0.010***
unexplained	
Years of Employment: Self-Employed	0.005
Years of Employment: Private Industry	-0.380***
Years of Employment: Public Service	-0.120***
Years of Employment: Civil Service	-0.002
noncontinuous employment-history	0.282***
Has Never Been Employed	0.001
Worker	0.015
Employee	0.085
Civil Servant	-0.007
Self-Employed	0.006
No training	0.012
Vocational Training	0.015
Master Craftperson, Polytechnics	-0.001
University	-0.001
Miscellaneous Training	-0.001
Married	0.127***
Widowed	0.126***
Divorced	-0.029***
Single	-0.014***
Children	-0.012
Region	-0.099***
Constant	0.709**
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.11
RIF-regression results at 50 % quantile - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.002
Years of Employment: Private Industry	0.008***
Years of Employment: Public Service	0.012***
Years of Employment: Civil Service	0.011***
noncontinuous employment-history	0.047
Has Never Been Employed	-0.157**
Worker	-0.127
Employee	0.113
Civil Servant	0.220
Self-Employed	-0.048
No Training	-0.145***
Vocational Training	-0.043**
Master Craftperson, Polytechnics	0.032
University	0.163***
Miscellaneous Training	-0.007
Married	0.082***
Widowed	0.092***
Divorced	-0.134***
Single	-0.040
Children	-0.009*
Region	-0.354***
Constant	6.984***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.12
RIF-regression results at 50 % quantile - women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.004
Years of Employment: Private Industry	0.028***
Years of Employment: Public Service	0.034***
Years of Employment: Civil Service	0.015*
noncontinuous employment-history	-0.554***
Has Never Been Employed	-0.288***
Worker	-0.165
Employee	-0.053
Civil Servant	0.637**
Self-Employed	-0.131
No Training	-0.174***
Vocational Training	-0.076**
Master Craftperson, Polytechnics	0.064
University	0.179***
Miscellaneous Training	0.006
Married	-0.202***
Widowed	-0.217***
Divorced	0.262***
Single	0.157***
Children	-0.004
Region	0.087**
Constant	6.275***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: ASID 2007, authors' estimations

Table A.13
Decomposition for 75 % quantile

	Log Own Pension
	b
overall	
men	7.534***
women	6.770***
difference	0.764***
explained	0.167***
unexplained	0.597***
explained	
Years of Employment: Self-Employed	-0.004**
Years of Employment: Private Industry	0.019*
Years of Employment: Public Service	-0.001***
Years of Employment: Civil Service	0.059***
noncontinuous employment-history	0.026
Has Never Been Employed	0.0001
Worker	-0.001
Employee	-0.020
Civil Servant	-0.002
Self-Employed	-0.0002
No training	0.042***
Vocational Training	-0.005***
Master Craftperson, Polytechnics	0.007
University	0.012***
Miscellaneous Training	0.000
Married	0.030***
Widowed	-0.013*
Divorced	0.002***
Single	0.001
Children	0.006*
Region	0.010***
unexplained	
Years of Employment: Self-Employed	-0.002
Years of Employment: Private Industry	-0.188***
Years of Employment: Public Service	-0.094***
Years of Employment: Civil Service	0.003
noncontinuous employment-history	0.062**
Has Never Been Employed	0.0004
Worker	0.026
Employee	0.103
Civil Servant	-0.006*
Self-Employed	0.001
No training	0.023**
Vocational Training	0.021
Master Craftperson, Polytechnics	-0.006***
University	-0.002
Miscellaneous Training	0.006**
Married	0.126***
Widowed	0.088***
Divorced	-0.019***
Single	-0.018***
Children	0.018
Region	-0.029***
Constant	0.483**
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.14
RIF-regression results at 75 % quantile - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.004**
Years of Employment: Private Industry	0.002*
Years of Employment: Public Service	0.004***
Years of Employment: Civil Service	0.022***
noncontinuous employment-history	-0.058
Has Never Been Employed	-0.065
Worker	-0.089
Employee	0.184
Civil Servant	-0.024
Self-Employed	-0.006
No Training	-0.152***
Vocational Training	-0.096***
Master Craftperson, Polytechnics	0.041
University	0.210***
Miscellaneous Training	-0.003
Married	0.095***
Widowed	0.046*
Divorced	-0.117***
Single	-0.024
Children	-0.012*
Region	-0.344***
Constant	7.431***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.15
RIF-regression results at 75 % quantile - women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.003*
Years of Employment: Private Industry	0.012***
Years of Employment: Public Service	0.021***
Years of Employment: Civil Service	0.017***
noncontinuous employment-history	-0.191***
Has Never Been Employed	-0.137***
Worker	-0.155**
Employee	-0.017
Civil Servant	0.323*
Self-Employed	-0.014
No Training	-0.209***
Vocational Training	-0.141***
Master Craftperson, Polytechnics	0.181***
University	0.274***
Miscellaneous Training	-0.104***
Married	-0.187***
Widowed	-0.171***
Divorced	0.134***
Single	0.224***
Children	-0.021***
Region	-0.216***
Constant	6.949***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: ASID 2007, authors' estimations

Table A.16
Decomposition for 90 % quantile

	Log Own Pension b
overall	
men	7.871***
women	7.112***
difference	0.749***
explained	0.210***
unexplained	0.539***
explained	
Years of Employment: Self-Employed	-0.008**
Years of Employment: Private Industry	-0.034*
Years of Employment: Public Service	0.002**
Years of Employment: Civil Service	0.127***
noncontinuous employment-history	0.009
Has Never Been Employed	0.0001
Worker	-0.001
Employee	-0.021**
Civil Servant	-0.010
Self-Employed	0.001
No training	0.088***
Vocational Training	-0.013***
Master Craftperson, Polytechnics	-0.013
University	0.041***
Miscellaneous Training	-0.0001
Married	0.033***
Widowed	-0.002
Divorced	0.003**
Single	-0.001
Children	-0.003
Region	0.012***
unexplained	
Years of Employment: Self-Employed	-0.009
Years of Employment: Private Industry	-0.226***
Years of Employment: Public Service	-0.176***
Years of Employment: Civil Service	-0.007
noncontinuous employment-history	0.054
Has Never Been Employed	0.0004
Worker	0.056
Employee	0.130*
Civil Servant	-0.008
Self-Employed	-0.0003
No training	-0.012
Vocational Training	-0.026
Master Craftperson, Polytechnics	-0.007
University	0.006
Miscellaneous Training	0.005
Married	0.170***
Widowed	0.097***
Divorced	-0.018***
Single	-0.026***
Children	0.067*
Region	0.011
Constant	0.459**
Observations	16519

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.17
RIF-regression results at 90 % quantile - men

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.008**
Years of Employment: Private Industry	-0.003*
Years of Employment: Public Service	-0.006**
Years of Employment: Civil Service	0.047***
noncontinuous employment-history	-0.020
Has Never Been Employed	-0.055
Worker	-0.054
Employee	0.195**
Civil Servant	-0.132
Self-Employed	0.046
No Training	-0.319***
Vocational Training	-0.261***
Master Craftperson, Polytechnics	-0.080
University	0.726***
Miscellaneous Training	-0.066
Married	0.105***
Widowed	0.007
Divorced	-0.150**
Single	0.037
Children	0.006
Region	-0.405***
Constant	7.948***
Observations	7280

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Table A.18
RIF-regression results at 90 % quantile - women

	Log Own Pension Coefficient
Years of Employment: Self-Employed	-0.004*
Years of Employment: Private Industry	0.009***
Years of Employment: Public Service	0.027***
Years of Employment: Civil Service	0.059***
noncontinuous employment-history	-0.135***
Has Never Been Employed	-0.134*
Worker	-0.193**
Employee	-0.060
Civil Servant	0.336
Self-Employed	0.050
No Training	-0.291***
Vocational Training	-0.206***
Master Craftperson, Polytechnics	0.087
University	0.564***
Miscellaneous Training	-0.154*
Married	-0.275***
Widowed	-0.231***
Divorced	0.095*
Single	0.411***
Children	-0.027***
Region	-0.453***
Constant	7.489***
Observations	9239

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: ASID 2007, authors' estimations

Appendix B

Long-run Effects of Career Interruptions - A Microsimulation Study

Table B.1
Out of Employment, Men

	(1) Out of Employment
Age	0.0263
Age^2	-0.000175
Number of children	0.0186
Duration last interruption	0.0120
Time since last interruption	-0.0468***
Time since last interruption^2	0.000740***
Qualification	-0.0745***
Experience full-time	-0.0265*
Experience part-time	0.0650**
Experience full-time^2	0.000519*
Experience part-time^2	-0.00719*
Married	-0.100*
East Germany	0.202***
Constant	-2.181***
Observations	26324

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table B.2
Out of Employment, Women

	(1) Out of Employment
Age	-0.160***
Age^2	0.00176***
Number of children	-0.124***
Duration last interruption	0.00315
Time since last interruption	-0.0501***
Time since last interruption^2	0.00100***
Qualification	-0.0446***
Experience full-time	-0.0209**
Experience part-time	-0.0314***
Experience full-time^2	-0.0000189
Experience part-time^2	0.000560*
Married	0.00547
East Germany	0.0452
Constant	2.589***
Observations	24698

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table B.3
Reentry work force, Men

	(1) Reentry work force
Age	0.0284
Age^2	-0.00114*
Number of children	-0.0197
Duration last interruption	-0.0452***
Qualification	0.202***
Experience full-time	0.0435**
Experience part-time	0.0361
Experience full-time^2	0.0000380
Experience part-time^2	-0.00141
Married	0.282***
East Germany	-0.175**
Constant	-0.206
Observations	3387

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEPv20 - SOEPv29

Table B.4
Reentry work force, Women

	(1) Reentry work force
Age	0.145***
Age^2	-0.00217***
Number of children	-0.0479*
Duration last interruption	-0.0213***
Qualification	0.0778***
Experience full-time	0.0130
Experience part-time	0.0802***
Experience full-time^2	0.000623*
Experience part-time^2	-0.00165***
Married	0.0183
East Germany	-0.0933*
Constant	-3.027***
Observations	8366

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

multicolumn2l*Source:* SOEPv20 - SOEPv29

TABLE B.5
Working hours, Men

	(1) Working hours
Age	-0.00695
Age^2	-0.00313***
Number of children	-0.0294
Duration last interruption	-0.145*
Duration last interruption^2	-0.00116
Time since last interruption	0.0231*
Time since last interruption^2	-0.0000705
Qualification	0.290***
Experience full-time	0.204***
Experience part-time	-0.277***
Experience full-time^2	0.00106
Experience part-time^2	0.0228***
Married	0.139
Constant	38.74***
Observations	22433

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table B.6
Working hours, Women

	(1) Working hours
Age	-0.0328
Age^2	-0.00437***
Number of children	-1.883***
Duration last interruption	-0.543***
Duration last interruption^2	0.0194***
Time since last interruption	0.300***
Time since last interruption^2	-0.00574***
Qualification	0.811***
Experience full-time	0.536***
Experience part-time	0.0511
Experience full-time^2	-0.00287**
Experience part-time^2	0.00589***
Married	-2.346***
Constant	30.74***
Observations	22512

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table B.7
Wage deviation, Men

	(1) Wage deviation
Age	-0.00663
Age^2	0.000222***
Number of children	0.0214***
Duration last interruption	-0.0443***
Duration last interruption^2	0.00201***
Time since last interruption	0.00343***
Qualification	0.0916***
Experience full-time	0.00582
Experience part-time	-0.0251***
Experience full-time^2	-0.000411***
Experience part-time^2	-0.000184
Married	0.0360***
Constant	-0.503***
Observations	22241

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table B.8
Wage deviation, Women

	(1) Wage deviation
Age	0.0154***
Age^2	-0.000162**
Number of children	0.0291***
Duration last interruption	-0.0102***
Duration last interruption^2	0.000108
Time since last interruption	0.00488***
Qualification	0.104***
Experience full-time	0.0107***
Experience part-time	-0.00147
Experience full-time^2	-0.000231***
Experience part-time^2	-0.0000317
Married	0.0203*
Constant	-0.930***
Observations	22287

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Appendix C

The Role of the Mini-job in the Long-Term Development of the Gender Pension Gap

Transition equation estimates

Table C.1
Transition estimation - full-time, men, no migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	2.829	(1.01)
L.Age sq.	-0.0595	(-1.30)
L.Number of children	-0.701	(-0.72)
L.Duration last interruption	8.564	(1.01)
L.Duration last interruption sq.	-1.930	(-0.81)
L.Time since interruption	-1.467	(-1.57)
L.Time since interruption sq.	0.0659	(1.59)
L.Qualification (Years)	0.776	(1.77)
L.Full-time exp.	0.605	(1.11)
L.Part-time exp.	4.406**	(2.79)
L.Full-time exp. sq.	-0.0118	(-1.06)
L.Part-time exp.sq.	-1.334	(-1.90)
L.Married	-1.981*	(-1.96)
Indicator East Germany	-12.62	(-0.03)
Constant	-40.29	(-0.90)
3		
L.Age	-0.0972	(-0.74)
L.Age sq.	0.00108	(0.80)
L.Number of children	0.000140	(0.00)
L.Duration last interruption	0.0909*	(2.05)
L.Duration last interruption sq.	-0.00299	(-1.08)
L.Time since interruption	-0.138***	(-10.73)
L.Time since interruption sq.	0.00257***	(7.71)
L.Qualification (Years)	-0.0937**	(-2.71)
L.Full-time exp.	-0.0206	(-0.58)
L.Part-time exp.	-0.0494	(-0.95)
L.Full-time exp. sq.	0.000125	(0.17)
L.Part-time exp.sq.	0.00212	(0.66)
L.Married	-0.120	(-1.20)
Indicator East Germany	0.175	(1.79)
Constant	0.882	(0.30)
4		
L.Age	-0.0103	(-0.03)
L.Age sq.	0.00162	(0.47)
L.Number of children	-0.0464	(-0.32)
L.Duration last interruption	-0.0650	(-0.44)
L.Duration last interruption sq.	0.00189	(0.33)
L.Time since interruption	-0.0539	(-1.24)
L.Time since interruption sq.	0.00168	(1.56)
L.Qualification (Years)	0.195*	(2.03)
L.Full-time exp.	-0.172*	(-2.50)
L.Part-time exp.	0.162*	(2.43)
L.Full-time exp. sq.	0.000219	(0.15)
L.Part-time exp.sq.	-0.00596	(-1.92)
L.Married	-0.00566	(-0.02)
Indicator East Germany	-0.291	(-0.90)
Constant	-5.716	(-0.74)
Observations	19037	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.2
Transition estimation - full-time, women, no migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	3.650*	(2.22)
L.Age sq.	-0.0357*	(-2.13)
L.Number of children	0.729	(1.70)
L.Duration last interruption	0.296	(1.30)
L.Duration last interruption sq.	-0.0143	(-1.03)
L.Time since interruption	-0.116	(-1.22)
L.Time since interruption sq.	0.00313	(1.18)
L.Qualification (Years)	-0.364	(-1.55)
L.Full-time exp.	-0.0292	(-0.22)
L.Part-time exp.	-0.0362	(-0.28)
L.Full-time exp. sq.	-0.00273	(-0.64)
L.Part-time exp.sq.	0.00125	(0.25)
L.Married	-0.356	(-0.59)
Indicator East Germany	0.148	(0.21)
Constant	-95.85*	(-2.38)
3		
L.Age	-0.364*	(-2.14)
L.Age sq.	0.00385*	(2.20)
L.Number of children	-0.386**	(-3.19)
L.Duration last interruption	0.00282	(0.07)
L.Duration last interruption sq.	-0.000256	(-0.12)
L.Time since interruption	-0.138***	(-7.85)
L.Time since interruption sq.	0.00265***	(5.63)
L.Qualification (Years)	-0.110*	(-2.53)
L.Full-time exp.	-0.0206	(-0.74)
L.Part-time exp.	-0.000219	(-0.01)
L.Full-time exp. sq.	-0.000130	(-0.20)
L.Part-time exp.sq.	-0.00154	(-1.04)
L.Married	0.267*	(2.11)
Indicator East Germany	-0.0871	(-0.70)
Constant	7.287	(1.80)
4		
L.Age	0.0681	(0.40)
L.Age sq.	-0.000478	(-0.28)
L.Number of children	0.223*	(2.34)
L.Duration last interruption	0.134**	(3.01)
L.Duration last interruption sq.	-0.00510*	(-1.97)
L.Time since interruption	-0.0694***	(-3.86)
L.Time since interruption sq.	0.00199***	(4.36)
L.Qualification (Years)	0.0700	(1.70)
L.Full-time exp.	-0.0363	(-1.45)
L.Part-time exp.	0.0977***	(3.60)
L.Full-time exp. sq.	-0.000131	(-0.21)
L.Part-time exp.sq.	-0.00228*	(-2.32)
L.Married	0.488***	(3.60)
Indicator East Germany	-0.732***	(-4.95)
Constant	-5.497	(-1.35)
Observations	9402	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.3
Transition estimation - not employed, men, no migration background

	(1)	
	Transisition between employment states	
1		
Constant	0	(.)
2		
L.Age	-0.0594	(-0.33)
L.Age sq.	-0.000611	(-0.33)
L.Number of children	-0.0734	(-0.99)
L.Duration last interruption	-0.251***	(-5.52)
L.Duration last interruption sq.	0.00708*	(2.52)
L.Qualification (Years)	0.195***	(3.80)
L.Full-time exp.	0.180***	(4.02)
L.Part-time exp.	0.0121	(0.19)
L.Full-time exp. sq.	-0.00195*	(-2.07)
L.Part-time exp.sq.	0.00220	(0.63)
L.Married	0.320*	(2.50)
Indicator East Germany	-0.0612	(-0.50)
Constant	-0.247	(-0.06)
3		
L.Age	0.683	(1.13)
L.Age sq.	-0.00711	(-1.15)
L.Number of children	0.302	(1.46)
L.Duration last interruption	-0.279*	(-2.51)
L.Duration last interruption sq.	0.00970*	(2.50)
L.Qualification (Years)	0.193	(1.25)
L.Full-time exp.	0.126	(1.11)
L.Part-time exp.	0.701**	(2.99)
L.Full-time exp. sq.	-0.00194	(-0.73)
L.Part-time exp.sq.	-0.0494	(-1.86)
L.Married	-0.0826	(-0.20)
Indicator East Germany	-0.112	(-0.26)
Constant	-22.51	(-1.55)
4		
L.Age	0.288	(0.49)
L.Age sq.	-0.00291	(-0.48)
L.Number of children	-0.100	(-0.34)
L.Duration last interruption	-0.0771	(-0.66)
L.Duration last interruption sq.	0.00108	(0.19)
L.Qualification (Years)	0.368*	(2.27)
L.Full-time exp.	-0.103	(-1.17)
L.Part-time exp.	0.535	(1.81)
L.Full-time exp. sq.	0.00198	(0.90)
L.Part-time exp.sq.	-0.0640	(-1.58)
L.Married	-0.280	(-0.60)
Indicator East Germany	-0.530	(-1.03)
Constant	-11.20	(-0.80)
Observations	2338	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.4
Transition estimation - not employed, women, no migration background

	(1) Transisition between employment states	
1		
2		
L.Age	0.311	(1.60)
L.Age sq.	-0.00444*	(-2.19)
L.Number of children	-0.283**	(-2.88)
L.Duration last interruption	-0.287***	(-7.84)
L.Duration last interruption sq.	0.00696***	(4.74)
L.Qualification (Years)	0.226***	(4.75)
L.Full-time exp.	0.105***	(4.00)
L.Part-time exp.	0.0511	(1.62)
L.Full-time exp. sq.	-0.000424	(-0.58)
L.Part-time exp.sq.	0.000604	(0.46)
L.Married	-0.246	(-1.81)
Indicator East Germany	0.507***	(3.68)
Constant	-8.349	(-1.80)
3		
L.Age	0.407	(1.57)
L.Age sq.	-0.00486	(-1.82)
L.Number of children	-0.0952	(-0.82)
L.Duration last interruption	-0.167***	(-4.12)
L.Duration last interruption sq.	0.00365*	(2.46)
L.Qualification (Years)	-0.00304	(-0.04)
L.Full-time exp.	0.00745	(0.22)
L.Part-time exp.	0.137***	(3.33)
L.Full-time exp. sq.	0.000415	(0.37)
L.Part-time exp.sq.	-0.00338	(-1.94)
L.Married	-0.00723	(-0.04)
Indicator East Germany	0.217	(1.01)
Constant	-11.43	(-1.83)
4		
L.Age	0.447*	(2.08)
L.Age sq.	-0.00563*	(-2.50)
L.Number of children	0.121	(1.63)
L.Duration last interruption	-0.166***	(-4.10)
L.Duration last interruption sq.	0.00298	(1.53)
L.Qualification (Years)	0.299***	(5.97)
L.Full-time exp.	0.0776**	(2.61)
L.Part-time exp.	0.203***	(6.04)
L.Full-time exp. sq.	-0.00123	(-1.17)
L.Part-time exp.sq.	-0.00477**	(-3.25)
L.Married	-0.192	(-1.20)
Indicator East Germany	-0.304	(-1.57)
Constant	-12.88*	(-2.53)
Observations	5289	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.5
Transition estimation - mini-job, men, no migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	-0.320	(-0.25)
L.Age sq.	0.00224	(0.17)
L.Number of children	0.799	(1.49)
L.Duration last interruption	0.454	(1.45)
L.Duration last interruption sq.	-0.0298	(-1.61)
L.Qualification (Years)	-0.384	(-1.04)
L.Full-time exp.	0.255	(1.05)
L.Part-time exp.	-1.016	(-1.81)
L.Full-time exp. sq.	-0.00201	(-0.33)
L.Part-time exp.sq.	0.123	(1.87)
L.Married	-2.318*	(-2.06)
Indicator East Germany	2.999*	(2.50)
Constant	7.987	(0.26)
3		
L.Age	0.0420	(0.04)
L.Age sq.	-0.000489	(-0.05)
L.Number of children	0.366	(0.82)
L.Duration last interruption	0.559*	(2.27)
L.Duration last interruption sq.	-0.0301*	(-2.25)
L.Qualification (Years)	-0.433	(-1.51)
L.Full-time exp.	0.128	(0.65)
L.Part-time exp.	-1.132*	(-2.12)
L.Full-time exp. sq.	-0.000216	(-0.04)
L.Part-time exp.sq.	0.122	(1.88)
L.Married	-2.831**	(-2.85)
Indicator East Germany	2.281*	(2.18)
Constant	1.378	(0.06)
4		
L.Age	-7.483	(-0.00)
L.Age sq.	0.143	(0.00)
L.Number of children	-28.15	(-0.00)
L.Duration last interruption	0.139	(0.00)
L.Duration last interruption sq.	-0.224	(-0.00)
L.Qualification (Years)	-6.653	(-0.00)
L.Full-time exp.	-16.43	(-0.00)
L.Part-time exp.	25.34	(0.00)
L.Full-time exp. sq.	0.216	(0.00)
L.Part-time exp.sq.	-3.889	(-0.00)
L.Married	132.6	(0.01)
Indicator East Germany	-97.98	(-0.00)
Constant	104.0	(0.00)
Observations	134	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.6
Transition estimation - mini-job, women, no migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	1.347	(1.64)
L.Age sq.	-0.0148	(-1.72)
L.Number of children	0.211	(0.72)
L.Duration last interruption	-0.128	(-0.97)
L.Duration last interruption sq.	0.00613	(1.05)
L.Qualification (Years)	0.333	(1.79)
L.Full-time exp.	0.118	(1.07)
L.Part-time exp.	-0.0463	(-0.29)
L.Full-time exp. sq.	-0.000922	(-0.27)
L.Part-time exp.sq.	0.000445	(0.05)
L.Married	-1.104*	(-2.04)
Indicator East Germany	0.792	(1.45)
Constant	-32.93	(-1.69)
3		
L.Age	0.481	(1.29)
L.Age sq.	-0.00459	(-1.20)
L.Number of children	0.130	(0.70)
L.Duration last interruption	0.0392	(0.47)
L.Duration last interruption sq.	-0.00259	(-0.70)
L.Qualification (Years)	-0.200	(-1.62)
L.Full-time exp.	0.0484	(0.78)
L.Part-time exp.	-0.229**	(-2.77)
L.Full-time exp. sq.	-0.00162	(-0.76)
L.Part-time exp.sq.	0.00795*	(2.18)
L.Married	-0.717*	(-2.00)
Indicator East Germany	0.333	(0.90)
Constant	-9.919	(-1.10)
4		
L.Age	2.248*	(2.25)
L.Age sq.	-0.0232*	(-2.20)
L.Number of children	0.172	(0.56)
L.Duration last interruption	0.239	(1.10)
L.Duration last interruption sq.	-0.0166	(-1.13)
L.Qualification (Years)	0.0432	(0.22)
L.Full-time exp.	0.0159	(0.14)
L.Part-time exp.	-0.0487	(-0.36)
L.Full-time exp. sq.	-0.00143	(-0.33)
L.Part-time exp.sq.	0.00354	(0.62)
L.Married	0.476	(0.66)
Indicator East Germany	0.0675	(0.10)
Constant	-55.98*	(-2.37)
Observations	291	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.7
Transition estimation - part-time, men, no migration background

	(1) Transisition between employment states	
1		
2		
L.Age	0.388	(0.81)
L.Age sq.	-0.00479	(-0.95)
L.Number of children	-0.0520	(-0.26)
L.Duration last interruption	0.193	(0.57)
L.Duration last interruption sq.	-0.0128	(-0.51)
L.Time since interruption	-0.0150	(-0.27)
L.Time since interruption sq.	0.00000955	(0.01)
L.Qualification (Years)	0.255	(1.76)
L.Full-time exp.	-0.0159	(-0.20)
L.Part-time exp.	-0.237**	(-2.73)
L.Full-time exp. sq.	0.00202	(0.96)
L.Part-time exp.sq.	0.0119***	(3.45)
L.Married	0.0155	(0.05)
Indicator East Germany	-0.222	(-0.60)
Constant	-9.569	(-0.83)
3		
L.Age	2231.3	(0.02)
L.Age sq.	-20.53	(-0.02)
L.Number of children	-27.90	(-0.00)
L.Duration last interruption	-35744.9	(-0.02)
L.Duration last interruption sq.	2233.6	(0.02)
L.Time since interruption	-1736.1	(-0.02)
L.Time since interruption sq.	22.31	(0.02)
L.Qualification (Years)	20.35	(0.00)
L.Full-time exp.	17.84	(0.01)
L.Part-time exp.	11.40	(0.00)
L.Full-time exp. sq.	-0.467	(-0.01)
L.Part-time exp.sq.	-0.173	(-0.00)
L.Married	17.72	(0.00)
Indicator East Germany	-300.5	(-0.00)
Constant	-27226.2	(-0.01)
4		
L.Age	-2.487*	(-2.55)
L.Age sq.	0.0234*	(2.34)
L.Number of children	-0.486	(-0.91)
L.Duration last interruption	-0.747	(-1.06)
L.Duration last interruption sq.	0.0559	(1.12)
L.Time since interruption	-0.0796	(-0.64)
L.Time since interruption sq.	-0.000527	(-0.16)
L.Qualification (Years)	-0.548	(-1.83)
L.Full-time exp.	-0.00680	(-0.05)
L.Part-time exp.	-0.0705	(-0.32)
L.Full-time exp. sq.	0.00355	(0.94)
L.Part-time exp.sq.	0.00976	(1.00)
L.Married	0.652	(0.72)
Indicator East Germany	0.142	(0.14)
Constant	64.37**	(2.70)
Observations	331	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.8
Transition estimation- part-time, women, no migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	0.00491	(0.03)
L.Age sq.	0.0000954	(0.06)
L.Number of children	-0.195*	(-2.47)
L.Duration last interruption	-0.0437	(-1.13)
L.Duration last interruption sq.	-0.000877	(-0.38)
L.Time since interruption	0.0419*	(2.53)
L.Time since interruption sq.	-0.000839*	(-2.00)
L.Qualification (Years)	0.0991**	(2.60)
L.Full-time exp.	0.0180	(0.84)
L.Part-time exp.	-0.0605*	(-2.26)
L.Full-time exp. sq.	-0.000707	(-1.10)
L.Part-time exp.sq.	0.000255	(0.29)
L.Married	-0.574***	(-4.73)
Indicator East Germany	0.234	(1.72)
Constant	-2.127	(-0.59)
3		
L.Age	0.239	(1.11)
L.Age sq.	-0.00195	(-0.88)
L.Number of children	0.0409	(0.39)
L.Duration last interruption	0.124**	(2.92)
L.Duration last interruption sq.	-0.00501*	(-2.45)
L.Time since interruption	-0.107***	(-3.95)
L.Time since interruption sq.	0.00208**	(2.86)
L.Qualification (Years)	-0.425***	(-6.48)
L.Full-time exp.	-0.0822**	(-2.75)
L.Part-time exp.	-0.0375	(-0.98)
L.Full-time exp. sq.	0.00152	(1.47)
L.Part-time exp.sq.	0.00119	(1.11)
L.Married	0.208	(0.90)
Indicator East Germany	-0.299	(-0.99)
Constant	-7.513	(-1.44)
4		
L.Age	-0.0773	(-0.37)
L.Age sq.	0.00106	(0.50)
L.Number of children	-0.366***	(-3.37)
L.Duration last interruption	-0.0479	(-1.17)
L.Duration last interruption sq.	0.00123	(0.65)
L.Time since interruption	-0.132***	(-5.29)
L.Time since interruption sq.	0.00240***	(3.53)
L.Qualification (Years)	-0.0869	(-1.59)
L.Full-time exp.	-0.0237	(-0.78)
L.Part-time exp.	-0.0838*	(-2.27)
L.Full-time exp. sq.	-0.000742	(-0.70)
L.Part-time exp.sq.	0.00150	(1.29)
L.Married	-0.632***	(-3.68)
Indicator East Germany	-0.311	(-1.23)
Constant	1.386	(0.28)
Observations	5775	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.9
Transition estimation - full-time, men, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	2.829	(1.01)
L.Age sq.	-0.0595	(-1.30)
L.Number of children	-0.701	(-0.72)
L.Duration last interruption	8.564	(1.01)
L.Duration last interruption sq.	-1.930	(-0.81)
L.Time since interruption	-1.467	(-1.57)
L.Time since interruption sq.	0.0659	(1.59)
L.Qualification (Years)	0.776	(1.77)
L.Full-time exp.	0.605	(1.11)
L.Part-time exp.	4.406**	(2.79)
L.Full-time exp. sq.	-0.0118	(-1.06)
L.Part-time exp.sq.	-1.334	(-1.90)
L.Married	-1.981*	(-1.96)
Indicator East Germany	-12.62	(-0.03)
Constant	-40.29	(-0.90)
3		
L.Age	-0.0972	(-0.74)
L.Age sq.	0.00108	(0.80)
L.Number of children	0.000140	(0.00)
L.Duration last interruption	0.0909*	(2.05)
L.Duration last interruption sq.	-0.00299	(-1.08)
L.Time since interruption	-0.138***	(-10.73)
L.Time since interruption sq.	0.00257***	(7.71)
L.Qualification (Years)	-0.0937**	(-2.71)
L.Full-time exp.	-0.0206	(-0.58)
L.Part-time exp.	-0.0494	(-0.95)
L.Full-time exp. sq.	0.000125	(0.17)
L.Part-time exp.sq.	0.00212	(0.66)
L.Married	-0.120	(-1.20)
Indicator East Germany	0.175	(1.79)
Constant	0.882	(0.30)
4		
L.Age	-0.0103	(-0.03)
L.Age sq.	0.00162	(0.47)
L.Number of children	-0.0464	(-0.32)
L.Duration last interruption	-0.0650	(-0.44)
L.Duration last interruption sq.	0.00189	(0.33)
L.Time since interruption	-0.0539	(-1.24)
L.Time since interruption sq.	0.00168	(1.56)
L.Qualification (Years)	0.195*	(2.03)
L.Full-time exp.	-0.172*	(-2.50)
L.Part-time exp.	0.162*	(2.43)
L.Full-time exp. sq.	0.000219	(0.15)
L.Part-time exp.sq.	-0.00596	(-1.92)
L.Married	-0.00566	(-0.02)
Indicator East Germany	-0.291	(-0.90)
Constant	-5.716	(-0.74)
Observations	19037	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.10
Transition estimation - full-time, women, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	129.2	(0.01)
L.Age sq.	-1.236	(-0.01)
L.Number of children	162.3	(0.01)
L.Duration last interruption	10.71	(0.00)
L.Duration last interruption sq.	-1.258	(-0.00)
L.Time since interruption	26.93	(0.01)
L.Time since interruption sq.	-1.011	(-0.01)
L.Qualification (Years)	1.641	(0.00)
L.Full-time exp.	236.2	(0.01)
L.Part-time exp.	411.7	(0.01)
L.Full-time exp. sq.	-6.018	(-0.01)
L.Part-time exp.sq.	-230.6	(-0.01)
L.Married	-411.2	(-0.00)
Indicator East Germany	-26.78	(-0.00)
Constant	-5882.6	(-0.01)
3		
L.Age	-0.356	(-0.97)
L.Age sq.	0.00388	(1.02)
L.Number of children	-0.388	(-1.60)
L.Duration last interruption	0.158	(1.49)
L.Duration last interruption sq.	-0.0113	(-1.63)
L.Time since interruption	-0.238***	(-6.39)
L.Time since interruption sq.	0.00505***	(4.99)
L.Qualification (Years)	-0.142	(-1.63)
L.Full-time exp.	0.0869	(1.46)
L.Part-time exp.	0.0221	(0.36)
L.Full-time exp. sq.	-0.00235	(-1.67)
L.Part-time exp.sq.	-0.00143	(-0.50)
L.Married	0.0438	(0.17)
Indicator East Germany	0.0624	(0.18)
Constant	6.263	(0.72)
4		
L.Age	0.406	(1.16)
L.Age sq.	-0.00335	(-0.93)
L.Number of children	0.0906	(0.47)
L.Duration last interruption	0.0699	(0.95)
L.Duration last interruption sq.	-0.00292	(-0.79)
L.Time since interruption	-0.113**	(-2.99)
L.Time since interruption sq.	0.00319**	(3.27)
L.Qualification (Years)	-0.0290	(-0.38)
L.Full-time exp.	-0.0278	(-0.62)
L.Part-time exp.	0.134**	(2.86)
L.Full-time exp. sq.	-0.000811	(-0.71)
L.Part-time exp.sq.	-0.00375*	(-2.36)
L.Married	0.824**	(3.03)
Indicator East Germany	-0.652	(-1.51)
Constant	-14.37	(-1.68)
Observations	1829	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.11
Transition estimation - not employed, men, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	0.371	(1.10)
L.Age sq.	-0.00483	(-1.39)
L.Number of children	0.0727	(0.60)
L.Duration last interruption	-0.337***	(-4.09)
L.Duration last interruption sq.	0.0120*	(2.46)
L.Qualification (Years)	0.304***	(3.59)
L.Full-time exp.	-0.0593	(-1.01)
L.Part-time exp.	-0.0638	(-0.45)
L.Full-time exp. sq.	0.00254	(1.86)
L.Part-time exp.sq.	0.0138	(0.82)
L.Married	0.545	(1.86)
Indicator East Germany	-0.288	(-0.92)
Constant	-8.846	(-1.10)
3		
L.Age	-0.213	(-0.29)
L.Age sq.	0.00152	(0.20)
L.Number of children	-0.580	(-1.84)
L.Duration last interruption	0.0556	(0.23)
L.Duration last interruption sq.	-0.0115	(-0.60)
L.Qualification (Years)	0.231	(1.20)
L.Full-time exp.	0.261	(1.19)
L.Part-time exp.	1.236**	(2.89)
L.Full-time exp. sq.	-0.00674	(-1.29)
L.Part-time exp.sq.	-0.179*	(-2.28)
L.Married	1.948	(1.85)
Indicator East Germany	-0.353	(-0.51)
Constant	-1.729	(-0.10)
4		
L.Age	-2.357*	(-1.97)
L.Age sq.	0.0240*	(2.03)
L.Number of children	-0.536	(-0.80)
L.Duration last interruption	0.276	(0.49)
L.Duration last interruption sq.	-0.0390	(-0.77)
L.Qualification (Years)	-0.202	(-0.46)
L.Full-time exp.	0.166	(0.54)
L.Part-time exp.	0.939	(1.35)
L.Full-time exp. sq.	-0.00362	(-0.60)
L.Part-time exp.sq.	-0.118	(-1.04)
L.Married	0.395	(0.31)
Indicator East Germany	0.0593	(0.05)
Constant	50.09	(1.76)
Observations	805	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.12
Transition estimation - not employed, women, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	0.147	(0.36)
L.Age sq.	-0.00303	(-0.71)
L.Number of children	-0.383*	(-1.99)
L.Duration last interruption	-0.238**	(-3.17)
L.Duration last interruption sq.	0.00562	(1.89)
L.Qualification (Years)	0.225*	(2.43)
L.Full-time exp.	0.124*	(2.31)
L.Part-time exp.	0.124	(1.87)
L.Full-time exp. sq.	-0.000756	(-0.49)
L.Part-time exp.sq.	0.00154	(0.52)
L.Married	-0.100	(-0.33)
Indicator East Germany	0.231	(0.65)
Constant	-4.607	(-0.47)
3		
L.Age	-0.248	(-0.55)
L.Age sq.	0.00199	(0.44)
L.Number of children	0.189	(1.03)
L.Duration last interruption	-0.0272	(-0.36)
L.Duration last interruption sq.	0.000297	(0.10)
L.Qualification (Years)	0.0989	(0.85)
L.Full-time exp.	0.0427	(0.69)
L.Part-time exp.	0.512***	(3.73)
L.Full-time exp. sq.	0.000538	(0.28)
L.Part-time exp.sq.	-0.0262**	(-2.66)
L.Married	-0.0368	(-0.09)
Indicator East Germany	0.481	(0.98)
Constant	1.610	(0.15)
4		
L.Age	0.766	(1.44)
L.Age sq.	-0.00994	(-1.72)
L.Number of children	0.0843	(0.66)
L.Duration last interruption	-0.120	(-1.63)
L.Duration last interruption sq.	0.00196	(0.57)
L.Qualification (Years)	0.161	(1.82)
L.Full-time exp.	0.0744	(1.34)
L.Part-time exp.	0.206**	(2.60)
L.Full-time exp. sq.	-0.000650	(-0.31)
L.Part-time exp.sq.	-0.00407	(-0.90)
L.Married	-0.176	(-0.54)
Indicator East Germany	-0.392	(-0.85)
Constant	-18.07	(-1.47)
Observations	1484	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEPv20 - SOEPv29

Table C.13
Transition estimation - mini-job, men, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	-0.320	(-0.25)
L.Age sq.	0.00224	(0.17)
L.Number of children	0.799	(1.49)
L.Duration last interruption	0.454	(1.45)
L.Duration last interruption sq.	-0.0298	(-1.61)
L.Qualification (Years)	-0.384	(-1.04)
L.Full-time exp.	0.255	(1.05)
L.Part-time exp.	-1.016	(-1.81)
L.Full-time exp. sq.	-0.00201	(-0.33)
L.Part-time exp.sq.	0.123	(1.87)
L.Married	-2.318*	(-2.06)
Indicator East Germany	2.999*	(2.50)
Constant	7.987	(0.26)
3		
L.Age	0.0420	(0.04)
L.Age sq.	-0.000489	(-0.05)
L.Number of children	0.366	(0.82)
L.Duration last interruption	0.559*	(2.27)
L.Duration last interruption sq.	-0.0301*	(-2.25)
L.Qualification (Years)	-0.433	(-1.51)
L.Full-time exp.	0.128	(0.65)
L.Part-time exp.	-1.132*	(-2.12)
L.Full-time exp. sq.	-0.000216	(-0.04)
L.Part-time exp.sq.	0.122	(1.88)
L.Married	-2.831**	(-2.85)
Indicator East Germany	2.281*	(2.18)
Constant	1.378	(0.06)
4		
L.Age	-7.483	(-0.00)
L.Age sq.	0.143	(0.00)
L.Number of children	-28.15	(-0.00)
L.Duration last interruption	0.139	(0.00)
L.Duration last interruption sq.	-0.224	(-0.00)
L.Qualification (Years)	-6.653	(-0.00)
L.Full-time exp.	-16.43	(-0.00)
L.Part-time exp.	25.34	(0.00)
L.Full-time exp. sq.	0.216	(0.00)
L.Part-time exp.sq.	-3.889	(-0.00)
L.Married	132.6	(0.01)
Indicator East Germany	-97.98	(-0.00)
Constant	104.0	(0.00)
Observations	134	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.14
Transition estimation - mini-job, women, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	2.711	(0.80)
L.Age sq.	-0.0315	(-0.84)
L.Number of children	-0.932	(-1.41)
L.Duration last interruption	0.126	(0.32)
L.Duration last interruption sq.	-0.0101	(-0.47)
L.Qualification (Years)	-0.303	(-0.69)
L.Full-time exp.	-0.000345	(-0.00)
L.Part-time exp.	-0.420	(-0.91)
L.Full-time exp. sq.	-0.00403	(-0.26)
L.Part-time exp.sq.	0.0263	(0.96)
L.Married	0.255	(0.18)
Indicator East Germany	-0.0225	(-0.02)
Constant	-54.63	(-0.71)
3		
L.Age	2.096	(1.57)
L.Age sq.	-0.0212	(-1.60)
L.Number of children	-1.021	(-1.90)
L.Duration last interruption	0.182	(0.66)
L.Duration last interruption sq.	-0.0136	(-0.98)
L.Qualification (Years)	-0.637	(-1.87)
L.Full-time exp.	-0.258	(-1.28)
L.Part-time exp.	-0.850*	(-2.24)
L.Full-time exp. sq.	0.00424	(0.84)
L.Part-time exp.sq.	0.0365	(1.55)
L.Married	0.0542	(0.05)
Indicator East Germany	-0.628	(-0.64)
Constant	-41.63	(-1.31)
4		
L.Age	2.768	(1.50)
L.Age sq.	-0.0296	(-1.56)
L.Number of children	-0.787	(-1.20)
L.Duration last interruption	0.237	(0.59)
L.Duration last interruption sq.	-0.0222	(-0.95)
L.Qualification (Years)	-0.736	(-1.73)
L.Full-time exp.	-0.294	(-1.22)
L.Part-time exp.	-1.074*	(-2.46)
L.Full-time exp. sq.	0.00666	(0.98)
L.Part-time exp.sq.	0.0516*	(2.02)
L.Married	0.0467	(0.04)
Indicator East Germany	-0.860	(-0.61)
Constant	-55.38	(-1.26)
Observations	73	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29, own calculations

Table C.15
Transition estimation - part-time, men, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	0.274	(0.66)
L.Age sq.	-0.00356	(-0.81)
L.Number of children	-0.0387	(-0.24)
L.Duration last interruption	-0.107	(-0.37)
L.Duration last interruption sq.	0.00825	(0.40)
L.Time since interruption	-0.0190	(-0.38)
L.Time since interruption sq.	0.000143	(0.11)
L.Qualification (Years)	0.0596	(0.52)
L.Full-time exp.	0.00745	(0.11)
L.Part-time exp.	-0.230**	(-2.93)
L.Full-time exp. sq.	0.000938	(0.53)
L.Part-time exp.sq.	0.0112***	(3.52)
L.Married	-0.151	(-0.50)
Indicator East Germany	-0.359	(-1.02)
Constant	-5.616	(-0.57)
3		
L.Age	-9.258**	(-2.73)
L.Age sq.	0.0930**	(2.72)
L.Number of children	-1.802	(-1.62)
L.Duration last interruption	1.340	(0.88)
L.Duration last interruption sq.	-0.0642	(-0.54)
L.Time since interruption	0.329	(0.93)
L.Time since interruption sq.	-0.00466	(-0.67)
L.Qualification (Years)	0.873	(1.27)
L.Full-time exp.	0.857*	(2.19)
L.Part-time exp.	0.975	(1.87)
L.Full-time exp. sq.	-0.0214*	(-2.08)
L.Part-time exp.sq.	-0.0465	(-1.72)
L.Married	2.890	(1.79)
Indicator East Germany	-12.92	(-0.02)
Constant	200.1**	(2.74)
4		
L.Age	-1.556*	(-1.99)
L.Age sq.	0.0147	(1.83)
L.Number of children	-0.564	(-1.34)
L.Duration last interruption	-0.416	(-0.90)
L.Duration last interruption sq.	0.0318	(0.95)
L.Time since interruption	-0.0909	(-1.00)
L.Time since interruption sq.	0.000902	(0.38)
L.Qualification (Years)	-0.560*	(-2.37)
L.Full-time exp.	0.0637	(0.61)
L.Part-time exp.	0.0425	(0.23)
L.Full-time exp. sq.	0.0000315	(0.01)
L.Part-time exp.sq.	0.00142	(0.16)
L.Married	0.374	(0.50)
Indicator East Germany	0.000669	(0.00)
Constant	39.94*	(2.13)
Observations	382	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29, own calculations

Table C.16
Transition estimation - part-time, women, migration background

	(1)	
	Transisition between employment states	
1		
2		
L.Age	0.395	(1.25)
L.Age sq.	-0.00452	(-1.39)
L.Number of children	-0.413*	(-2.33)
L.Duration last interruption	0.0869	(1.36)
L.Duration last interruption sq.	-0.00218	(-0.75)
L.Time since interruption	0.000736	(0.02)
L.Time since interruption sq.	0.000456	(0.48)
L.Qualification (Years)	0.137	(1.73)
L.Full-time exp.	0.0399	(0.93)
L.Part-time exp.	0.00803	(0.15)
L.Full-time exp. sq.	0.000154	(0.12)
L.Part-time exp.sq.	-0.0000365	(-0.02)
L.Married	-0.438	(-1.66)
Indicator East Germany	0.473	(1.15)
Constant	-11.25	(-1.48)
3		
L.Age	-0.323	(-0.75)
L.Age sq.	0.00447	(1.03)
L.Number of children	0.529*	(2.34)
L.Duration last interruption	0.119	(1.56)
L.Duration last interruption sq.	-0.00296	(-1.00)
L.Time since interruption	-0.138	(-1.89)
L.Time since interruption sq.	0.00280	(1.36)
L.Qualification (Years)	-0.0913	(-0.78)
L.Full-time exp.	-0.0401	(-0.69)
L.Part-time exp.	0.174	(1.38)
L.Full-time exp. sq.	0.00261	(1.44)
L.Part-time exp.sq.	-0.00857	(-1.57)
L.Married	0.609	(0.96)
Indicator East Germany	-0.677	(-0.56)
Constant	1.138	(0.11)
4		
L.Age	0.185	(0.42)
L.Age sq.	-0.00146	(-0.32)
L.Number of children	0.109	(0.58)
L.Duration last interruption	-0.100	(-1.59)
L.Duration last interruption sq.	0.00374	(1.76)
L.Time since interruption	-0.154**	(-2.75)
L.Time since interruption sq.	0.00354*	(2.30)
L.Qualification (Years)	-0.0302	(-0.30)
L.Full-time exp.	-0.0279	(-0.52)
L.Part-time exp.	-0.136	(-1.93)
L.Full-time exp. sq.	-0.000244	(-0.12)
L.Part-time exp.sq.	0.00322	(1.46)
L.Married	-0.127	(-0.34)
Indicator East Germany	-0.123	(-0.18)
Constant	-5.747	(-0.55)
Observations	1039	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29, own calculations

Working hours equation estimates

Table C.17
Working hours estimation - full-time, men

	(1) Working hours	
L.Age	0.116	(1.41)
L.Age sq.	-0.000775	(-0.90)
L.Number of children	0.0270	(0.71)
L.Duration last interruption	-0.0983	(-1.72)
L.Duration last interruption sq.	0.00217	(0.62)
L.Time since interruption	-0.0294**	(-3.28)
L.Time since interruption sq.	0.000516*	(2.17)
L.Qualification (Years)	0.0489	(1.10)
L.Full-time exp.	0.00849	(0.26)
L.Part-time exp.	-0.155**	(-2.91)
L.Full-time exp. sq.	-0.000476	(-0.77)
L.Part-time exp.sq.	-0.000563	(-0.16)
Married	0.144	(1.67)
Constant	36.10***	(20.60)
Observations	18331	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.18
Working hours estimation - full-time, women

	(1) Working hours	
L.Age	-0.0625	(-0.61)
L.Age sq.	0.00108	(1.03)
L.Number of children	-0.394***	(-4.97)
L.Duration last interruption	-0.00648	(-0.13)
L.Duration last interruption sq.	-0.00148	(-0.55)
L.Time since interruption	0.00702	(0.56)
L.Time since interruption sq.	0.00000125	(0.00)
L.Qualification (Years)	0.142**	(2.69)
L.Full-time exp.	0.165***	(5.92)
L.Part-time exp.	-0.370***	(-11.39)
L.Full-time exp. sq.	-0.00397***	(-6.74)
L.Part-time exp.sq.	0.0101***	(8.14)
Married	-0.312**	(-2.89)
Constant	37.04***	(15.29)
Observations	10996	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

TABLE C.19
Working hours estimation - part-time, men

	(1)	
	Working hours	
L.Age	-0.253	(-0.36)
L.Age sq.	0.000805	(0.11)
L.Number of children	0.435	(1.16)
L.Duration last interruption	-0.942	(-1.90)
L.Duration last interruption sq.	0.0528	(1.38)
L.Time since interruption	0.166*	(1.98)
L.Time since interruption sq.	-0.00313	(-1.42)
L.Qualification (Years)	0.258	(0.89)
L.Full-time exp.	0.347*	(2.08)
L.Part-time exp.	-0.102	(-0.62)
L.Full-time exp. sq.	-0.00615	(-1.68)
L.Part-time exp.sq.	0.0132*	(2.07)
Married	-0.0933	(-0.13)
Constant	27.09	(1.65)
Observations	403	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEPv20 - SOEPv29

Table C.20
Working hours estimation - part-time, women

	(1)	
	Working hours	
L.Age	0.695***	(4.28)
L.Age sq.	-0.00789***	(-4.79)
L.Number of children	-0.484***	(-5.11)
L.Duration last interruption	-0.0368	(-0.68)
L.Duration last interruption sq.	-0.00105	(-0.41)
L.Time since interruption	0.0953***	(4.24)
L.Time since interruption sq.	-0.00195**	(-3.11)
L.Qualification (Years)	0.563***	(6.95)
L.Full-time exp.	0.219***	(5.28)
L.Part-time exp.	0.0988*	(2.48)
L.Full-time exp. sq.	-0.00200	(-1.58)
L.Part-time exp.sq.	-0.000625	(-0.56)
Married	-1.375***	(-6.14)
Constant	1.274	(0.32)
Observations	6590	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Wage equation estimates

TABLE C.21
Wage estimation - men, regular employment

	(1)	
	Relative deviation from average wage	
L.Age	0.00933	(0.94)
L.Age sq.	0.0000325	(0.32)
L.Duration last interruption	-0.0448***	(-6.98)
L.Duration last interruption sq.	0.00174***	(4.15)
L.Time since interruption	0.00200	(1.93)
L.Time since interruption sq.	0.0000556*	(1.97)
L.Qualification (Years)	0.153***	(27.07)
L.Number of children	0.0224***	(4.78)
L.Full-time exp.	0.00984*	(2.50)
L.Part-time exp.	-0.0152*	(-2.57)
L.Full-time exp. sq.	-0.000429***	(-5.72)
L.Part-time exp.sq.	-0.000579	(-1.67)
L.Married	0.0320**	(3.08)
L.Indicator East Germany	-0.290***	(-13.59)
Constant	-1.124***	(-5.31)
Observations	19548	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

TABLE C.22
Wage estimation - women, regular employment

	(1)	
	Relative deviation from average wage	
L.Age	0.0136	(1.62)
L.Age sq.	-0.000143	(-1.68)
L.Duration last interruption	-0.0135***	(-3.86)
L.Duration last interruption sq.	0.000373*	(2.14)
L.Time since interruption	0.00668***	(6.56)
L.Time since interruption sq.	-0.0000554	(-1.86)
L.Qualification (Years)	0.150***	(30.13)
L.Number of children	0.0231***	(4.05)
L.Full-time exp.	0.00845***	(3.65)
L.Part-time exp.	-0.00185	(-0.77)
L.Full-time exp. sq.	-0.000162**	(-3.09)
L.Part-time exp.sq.	0.00000949	(0.13)
L.Married	0.000224	(0.02)
L.Indicator East Germany	-0.241***	(-12.44)
Constant	-1.007***	(-5.05)
Observations	18427	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29

Table C.23
Wage estimation - men, mini-job

	(1) Fraction of mini-job boundary wage	
proportion		
L.Age	-0.0999	(-0.54)
L.Age sq.	0.00122	(0.67)
L.Duration last interruption	-0.150***	(-3.68)
L.Duration last interruption sq.	0.00595**	(2.89)
L.Time since interruption	-0.0571	(-1.36)
L.Time since interruption sq.	0.00215	(1.84)
L.Qualification (Years)	0.0675	(1.23)
L.Number of children	-0.0518	(-0.55)
L.Full-time exp.	-0.0222	(-0.53)
L.Part-time exp.	0.176***	(3.92)
L.Full-time exp. sq.	0.000254	(0.26)
L.Part-time exp.sq.	-0.00687***	(-3.65)
L.Married	0.511***	(3.78)
L.Indicator East Germany	-0.425**	(-2.88)
Constant	1.979	(0.43)
oneinflate		
L.Age	-0.818*	(-2.29)
L.Age sq.	0.00683	(1.95)
L.Duration last interruption	-0.115	(-1.29)
L.Duration last interruption sq.	0.00779	(1.65)
L.Time since interruption	0.0683	(1.20)
L.Time since interruption sq.	-0.000405	(-0.27)
L.Qualification (Years)	0.448***	(4.22)
L.Number of children	0.0302	(0.16)
L.Full-time exp.	-0.0346	(-0.50)
L.Part-time exp.	0.197*	(2.27)
L.Full-time exp. sq.	0.00298	(1.79)
L.Part-time exp.sq.	-0.00899*	(-2.13)
L.Married	0.151	(0.57)
L.Indicator East Germany	-0.513	(-1.66)
Constant	20.28*	(2.32)
zeroinflate		
Constant	-1.045***	(-7.52)
ln_phi		
Constant	1.471***	(15.96)
Observations	417	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: SOEPv20 - SOEPv29

Table C.24

Wage estimation - women, mini-job

	(1) Fraction of mini-job boundary wage	
proportion		
L.Age	-0.0668	(-0.92)
L.Age sq.	0.000608	(0.85)
L.Duration last interruption sq. interruption	0.0141	(1.27)
L.Duration last interruption sq.	-0.000683	(-1.50)
L.Time since interruption	0.0569***	(5.69)
L.Time since interruption sq.	-0.00106***	(-3.53)
L.Qualification (Years)	-0.0376	(-1.72)
L.Number of children	0.0724*	(2.00)
L.Full-time exp.	0.00244	(0.24)
L.Part-time exp.	0.00729	(0.57)
L.Full-time exp. sq.	-0.000206	(-0.58)
L.Part-time exp.sq.	-0.0000278	(-0.07)
L.Married	0.471***	(6.27)
L.Indicator East Germany	-0.359***	(-4.15)
Constant	1.750	(0.97)
oneinflate		
L.Age	-0.184	(-1.53)
L.Age sq.	0.00137	(1.15)
L.Duration last interruption	-0.0178	(-0.83)
L.Duration last interruption sq.	0.000286	(0.29)
L.Time since interruption	0.0714***	(4.37)
L.Time since interruption sq.	-0.00161***	(-3.49)
L.Qualification (Years)	0.167***	(4.67)
L.Number of children	-0.138*	(-2.30)
L.Full-time exp.	0.0452**	(2.62)
L.Part-time exp.	0.0410	(1.83)
L.Full-time exp. sq.	-0.000448	(-0.74)
L.Part-time exp.sq.	-0.000478	(-0.69)
L.Married	0.107	(0.77)
L.Indicator East Germany	-1.036***	(-5.29)
Constant	3.868	(1.30)
zeroinflate		
Constant	-1.076***	(-21.25)
ln_phi		
Constant	1.204***	(36.68)
Observations	3112	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SOEPv20 - SOEPv29