Life Cycle Cost of Overconfidence: Evidence from Maternity Leave Reforms

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Abstract

This paper investigates the life cycle costs of overconfidence in future employment possibilities, focusing on females who experience child-related career breaks. To estimate these costs, I develop a novel strategy to identify expectations about employment prospects within a life cycle model of female labor supply and human capital accumulation. Reactions to a discontinuity in the future expected value of non-employment caused by the end of an employment protection allows for identification of expectations. In addition, reforms that exogenously vary the length of this protection period permit to separately identify each of expectations, job-arrival rates, and preferences. In line with suggestive evidence, the estimated life cycle model indicates that expectations are substantially biased: on average women expect the half-yearly job arrival rate to be twice the actual rate. This overconfidence prolongs the average child related career break by eight months, resulting in a larger share of mothers staying non-employed beyond the protection period. The implications of forgone wages and human capital are large, since overconfidence decreases life-time earnings from employment by 14%.

JEL: D84, J24, H30

Keywords: biased beliefs, labor supply, dynamic discrete choice, identification, maternity leave

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1 Introduction

Overconfidence is a well known human bias. Drivers overestimate how safe they drive, students overestimate their humor, grammar and logic skills with respect to others, and finance professionals are overconfident in their predictions of the stock market.[1] In the labor market, individuals might express overconfidence about their future employment prospects. The costs of such an optimistic bias might be especially high for mothers who interrupt their working careers after giving birth to a child.[2] If these mothers are too optimistic about their employment prospects, they might not return during the period that their job is protected by maternity leave, although optimal in the absence of a bias. This causes them to rely on new employment offers later on, for which the arrival probability is lower than they expect. Therefore, overconfidence in employment prospects is likely to prolong child-related employment interruptions, thus significantly increasing the career costs of having children. Previous literature acknowledges the importance of potentially biased expectations, but does not identify these within the context of child-related career breaks or quantifies their consequences for the working careers of mothers.

In this paper, I develop a life cycle model of female labor supply and human capital accumulation, derive a strategy to identify expectations within this model, and quantify the costs of overestimating employment prospects. To estimate the model, I use survey data from the German Socio-Economic Panel Study (SOEP), since German maternity leave regulations provides an ideal environment to identify the key parameters of the model. The identification approach exploits a discontinuity in the future expected value of non-employment, caused by the end of the employment protection. In addition, several policy reforms, which changed the length of the employment protection, created groups comparable to counterfactual situations where individuals face the discontinuity at different points in time. Using these reforms, it is possible to separately identify expectations, real job arrival rates, and preferences.

The deployed life cycle model nests the rational, and therefore unbiased, expectation approach, which is standard in the literature on life cycle models of female labor supply. This allows testing the rational expectations hypothesis directly. In a second step, I quantify the life cycle costs of these biased expectations. Holding the preference parameters constant, but restricting expectations to be rational, I simulate life cycle choices and examine the welfare costs of being too overconfident with regards to future employment possibilities. In a last step, I examine possible policy reforms that help to reduce or overcome these costs.

[1] See Svenson (1981), Kruger & Dunning (1999) and Ben-David et al. (2013). (De Bondt & Thaler, 1995, p. 389) even conclude, "perhaps the most robust finding in the psychology of judgment is that people are overconfident."

[2] Children are one important factor for the career dynamics of women. This is reflected by the average employment rates across OECD countries, which are 11 percent lower for women with at least one child (aged 0-14) than for women without a child in 2014. The career costs of having children can be high, for instance, Adda et al. (2017) estimate that fertility reduces the net present value of income by 35%.

In the first part of the paper, I develop a life cycle model of female labor supply (see for example Keane et al., 2011).[3] In my model, women make half-yearly labor supply choices facing labor market frictions. To enter employment after being non-employed, they have to draw on a job offer that they only receive with a certain probability. In contrast to a standard life cycle framework, I explicitly model expectations about the future job offer arrival rate. These expectations are crucial, when deciding whether or not to return within the employment-protected period. If an individual overestimates[4] her future job opportunities, she might not return during the employment protection and, thus, eventually faces real labor market frictions. Having overestimated her chances to receive a job offer, the career break is, on average, longer than expected by the individual. Because on-the-job human capital depreciates when being non-employed, longer non-employment spells are more costly for careers in the model.

In the second part of the paper, I introduce a novel approach to identify expectations about the future job arrival rate within the structural model. The approach exploits a discontinuity in the employment probability introduced by the end of the employment protection. At the end of this protection, the possibilities to re-enter employment change from returning to a guaranteed job to being reliant on a future job offer. Therefore, the probability to be able to choose employment in the subsequent period changes from almost 100%[5] to an unknown level when staying out of employment. This creates a discontinuity in the future expected value of non-employment. The group of mothers, who, in absence of labor market frictions, prefer to be non-employed beyond the end of the employment protection, considers returning earlier due to this discontinuity. The higher that a woman expect her future job offer probability to be – in other words the less severe the discontinuity in the future expected value of non-employment is – the less likely they are to return during the employment-protection period. Exploiting the excess mass of mothers returning right at the end of the employment-protection informs about their average expectation of their future job offer probability.[6] A large mass indicates that women expect future job offers to be rather rare.

[3]Papers employing a life cycle model of female labor supply include, for example, Blundell et al. (2016) who focus on human capital accumulation through the life Cycle, Adda et al. (2017) who evaluate how fertility influences occupational Choices, and Low et al. (2010) who investigate the influence of different types of risks that individuals face in their working life.

[4]Throughout this paper I use the terms overconfidence and overestimation interchangeably. I define overconfidence as expecting the rate of job offers arrivals to be higher than the true arrival rate.

[5]Individuals in employment protection do face the risk of a plant closure and, thus, the probability to be able to choose employment is less than 100%.

[6]The identification approach has some similarity with the literature on bunching (see Saez (2010) and Kleven & Waseem (2013)). The classical bunching approach would use a kink or notch in the tax schedule to recover underlying labor supply elasticities. In contrast, this paper uses a discontinuity over time in an employment guarantee. Additionally, the counterfactual situation of not having this discontinuity is available, since policy reforms prolonged the length of employment protection over the years. Another paper using bunching to identify welfare costs of behavioral elements instead of elasticities is Rees-Jones (2017). He tries to quantify the tax evasion costs introduced by loss-aversion when individuals owes taxes at the end of a tax year instead of receiving a refund.

To separately identify expectations, the real job offer rate and preferences from choice data, I additionally exploit several reforms of the German maternity leave regulations. These reforms first extend the employment protection period from 1 year to 1.5 years and then to 3 years, making them ideally suited for identification. The three different policy regimes create three groups of individuals facing different employment guarantees when the youngest child is between 1 and 1.5 years old. Employment rates of mothers in the regime with the longest lasting employment protection aid the identification of leisure preferences depending on the age of the youngest child. This is a result of these mothers not facing the labor market frictions until their youngest child turns three. Their returns to employment during this time are, therefore, strongly driven by their preferences. Using the differences in the length of employment protection, the real job offer rate can be identified. The difference in the average employment rates of individuals who do enjoy employment protection and who do not, due to being in different policy regimes, reflects how strongly mothers are restricted in their employment decision without the protection.

In the third part of the paper, I estimate the model and quantify the career costs of overconfidence. Half-yearly job arrival rates, as also shown by descriptive evidence, are quite low at around ten percent.[7] Individuals expect the job arrival rates to be more than twice as high, on average. These findings are in line with the suggestive evidence constructed from several questions of the SOEP questionnaire. Simulating the model once with the estimated expectations and once with rational expectations allows to quantify the costs of overconfidence. Under biased expectations, child related career breaks are, on average, 8 months longer. Women lose between 13% and 17% of the net present value of earnings from employment. The net present value in household consumption is much lower, lying between 3% and 4%. There are two main reasons for this difference. First, partners contribute the larger share to the overall household income, since they are mostly working full-time (and do not interrupt their career due to childbrith), while mothers re-entering the labor market typically work part-time. Second, the German tax system, with its joint taxation system, heavily taxes second earner income. The simulations also show that the costs of overconfidence decrease with the length of the employment protection.

The life cycle loss in earnings from employment due to biased expectations are meaningful from a public economics perspective. They resemble losses in income taxation in addition to the possible social security provided to mothers who have not returned to employment due to their biased expectations. In addition, the consequences for the individual are substantial: The lost life time earnings translate into lower pension benefits making them more vulnerable to poverty in retirement. The consequences might justify interventions by policy makers. Potential policies might provide

[7] These low offer rate estimates are not uncommon for the German labor market. Haan & Prowse (2017), for example, find similar values in a half-yearly model about family labor supply.

more information about employment prospects after child-related career breaks, for instances by introducing mandatory consulting meetings with an employment agency. Other measures might to financially incentivize returning within the employment protection, for example by providing in-work benefits toward the end of the employment protection.

Contribution to the literature

This work contributes to several streams in the literature: it contributes to the literature on overconfidence and its consequences; to the literature focusing on employment and reactions to welfare programs in a life cycle setting; and to the growing literature on behavioral public economics. There is little evidence of overconfidence and its consequences using a revealed preference approach outside of laboratory experiments. Since the work of Tversky & Kahneman (1974), which introduces a theory for their finding that individuals exhibit systematic biases when acting under uncertainty, the literature on social psychology and organizational behavior[8] has intensively analyze overconfidence. An introduction into the literature's link to economic questions is provided by Malmendier & Taylor (2015).[9] The majority of the findings stem from experiments, since most surveys capture expectations too broadly to provide convincing evidence on overconfidence. Although laboratory experiments are ideal for exploring behavior and testing possible theories about the decision making process, they might not be well suited to quantify real economic consequences. This paper closes this gap by identifying expectations from observed choice data within a life-cycle model of labor supply.

The labor economics literature investigating expectations outside experiments can be divided into two parts. One part uses subjective data in reduced form analysis to determine the impact of expectations on labor outcomes. Most of this research investigates how future earnings and labor market attachment expectations influence education and other investment in human capital decisions. For example, Sandell & Shapiro (1980) and Shaw & Shapiro (1987) show that individuals, who do not expect strong future labor attachment, invest less in human capital than individuals with stronger expected attachment. This is further underlined by Gronau (1988) and Blau & Ferber (1991). The other part of the literature concentrates on testing more directly if expectations are "rational" by comparing surveyed expectations with actual behavior. For instance, Hamermesh

[8]Moore & Healy (2008) survey this literature.

[9]For seminal work, see, for example, Svenson (1981) who finds that 83% of participants in a laboratory experiment stated that they are in the top 30% regarding driving safety, Kruger & Dunning (1999) who find that students who scored in the bottom quartile (and thus find themselves in the 12*th* percentile, on average) in tests regarding humor, grammar, and logic skills, believe themselves to be in the 63*rd* percentile of the distribution, and Ben-David et al. (2013) who show that only 36.3% of the time the S&P500 falls into the 80% confidence interval provided by CFOs of mid-size and large U.S. corporations. Further examples include Weinstein (1980) and Slovic (2000). The literature mainly uses three definitions of overconfidence: (1) the overestimation of the probability of positive events; (2) the overestimation of one's performance compared to others; and (3) the overestimation of the precision of one's information. The model and identification approach of this paper correspond to the first definition.

(1985), Bernheim (1988), and Hurd et al. (2004) find individuals are able to predict their retirement age.

The majority of these studies use questions only allowing for yes-no answers to elicit expectations. Manski (1990) shows that even in the absence of aggregate shocks, binary expectations questions are ill-equipped for investigating the hypothesis of rational expectations.[10] In addition, nearly all these questions are mixing pure expectations of exogenous events with preferences that prevent a clear distinction between these two factors. In contrast, the model and identification strategy presented in this paper do not rely on questions to elicit expectations and, therefore, does not suffer from these problems that are related to survey questions. It also allows clearly differentiating between biased expectations of exogenous future events and changes in preferences.

A stronger focus on overconfidence in future employment prospects represents the work of Spinnewijn (2015). He examines the optimal unemployment insurance design when job seekers overestimate their chances of finding employment. In addition to a theoretical analysis of how to adjust the Baily formula (Baily, 1978; Chetty, 2006) when employment seekers express overconfidence, Spinnewijn (2015) calibrates a job search model with various degrees of biased expectations. He finds that overconfident agents are less responsive to future incentives and shows that this can result in optimal unemployment benefits to increase over the unemployment spell. Complementing this work, this paper concentrates on the individual career costs of mothers in a life cycle framework. Since the majority of female career breaks are family-related, adjusting maternity-leave policies seems preferable to adjusting unemployment insurance in this case.

Another empirical investigation of overconfidence and its consequences in labor supply contexts is Hoffman & Burks (2017). They investigate the overconfidence in productivity by truck drivers, finding it contributes to fewer employees quitting. Overall this causes the welfare to increase, since the companies face large initial training costs when hiring new drivers. I extend this research by discussing the effect of overconfidence on the career development of mothers. In contrast to Hoffman & Burks (2017), my results indicate that there can be substantial costs when individuals are too optimistic about their future employment possibilities.

This paper also contributes to the literature focusing on employment and welfare of mothers in a life cycle context. Adda et al. (2017), using a life cycle model of occupational choice, find that family-oriented women already choose occupations that are family friendly but not necessarily well

[10] A short example should illustrate this statement. Assume a single event A occurs with the probability of 51%. If the event is realized, a subject will work the next period, otherwise she will spend time in home production. If asked if they will expect to be working next period, all subjects will answer with "yes," since "no" is more unlikely. On average, this results in a discrepancy between the stated expectations and realizations of 49 percentage points. For a more general discussion of the importance of expectations in economics and their measurement see Manski (2004).

paid. They estimate the cost of having children to be about 30% of lifetime income. Some of these costs stem also from lost earnings and depreciation of human capital during career breaks. Blundell et al. (2016) estimate a model of human capital accumulation and depreciation that points to very low human capital accumulation in part-time employment and, therefore, stagnating careers for women who do not work full-time. Employing a similar model of life cycle labor supply, I extend their findings by dividing career costs into expected and unexpected ones. While anticipated career costs do not necessarily justify policy interventions when markets are close to perfect, biased expectations can be regarded as market imperfections and, thus, justify additional regulations. An example of a more harmless intervention is the direct provision of information, for example in form of letters. These seem to work well in the some fields of public economics (see for example Bhargava & Manoli (2015), and Duflo & Saez (2003), and for the German context Dolls et al. (2016)).

In addition, this paper relates to the growing literature of behavioral public economics. Because optimal policy design depends on the behavior of individuals, ignoring behavioral insights may lead to wrong policy recommendations. Some behavioral insights can also lead to more efficient policies, such as providing additional information or commitment devices, which might have otherwise been ignored. In the context of labor supply, DellaVigna et al. (2017) exploit a reform of unemployment benefits in Hungary, showing that job seekers have reference-dependent preferences. They argue that in this case a multi-step unemployment insurance is optimal. DellaVigna & Paserman (2005) and Chan (2017) investigate time-inconsistent preferences in the form of hyperbolic-discounting. The former find that measurements of impatience of job seekers and their respective unemployment lengths are in line with the hyperbolic-discounting model. Chan (2017) identifies discounting parameters with data from a field experiment. He finds evidence for a welfare-trap. Individuals who are not currently employed, postpone their decision to start to work due to time-inconsistent behavior. I extend this literature by determining how expectations might contribute to the length of non-employment durations.

The paper proceeds as follows. Section 2 discusses the institutional framework. Section 3 describes the data. Section 4 presents some descriptive characteristic of the data and provides suggestive evidence for the biased expectations about future employment prospects. Section 5 develops the structural life cycle model. Section 6 discusses the identification and estimation of the model parameters, in particular the identification of beliefs. Section 7 presents the results and discusses their implications. Section 8 concludes.

2 Maternity Leave policy in Germany

German maternity leave regulations provides an ideal environment to identify overconfidence with respect to future employment possibilities and quantify its consequences. Several policy reforms extended primarily the length of time that an individual's job is protected during parental leave, providing exogenous variation for identification. In total, I exploit three major expansions of maternity leave coverage between the years 1986 and 1993, which I summarize as three major policy regimes.[11] The objective of these reforms was twofold. First, they intended to encourage mothers to spend more time with their children during their early development. Second, they tried to increase maternal labor market attachment, since a longer employment protection period was seen as easing the labor market return. In addition, the last policy regime extended employment protection to three years, creating a group of mothers who do not face labor market frictions for this period. This allows for easier identification of leisure preferences depending on the age of the child up to year three, since returning rates within the employment protection can inform about preferences in the absence of labor market frictions.

Since the late-1960s, mothers were entitled to have 14 weeks of paid leave around childbirth. Typically, this time period was divided into six weeks before the (expected) birth and eight weeks after, during which women were generally not allowed to work. While on leave, employees must not be dismissed and were guaranteed a comparable job to their previous held one upon returning to work. During the 14 weeks, women received the average income of the three month before entering maternity leave, resulting in an income replacement rate of 100%. The core of this law is still effective in 2017.[12] In the late-1970s, the first major reform prolonged maternity leave coverage, extending the employment protection period to six months after childbirth, while a new maternity leave payment for the time between the 8^{th} week and the end of the 6^{th} month was introduced. In this period, women, who were employed before having a child, received DM 750[13] per month.

The reforms exploited in this paper started in January 1986. An overview of these are in table 1. The first reform expanded the employment protection and maternity benefit period from six to ten months at the beginning of 1986 and then further to 12 months in January 1988.[14] Maternity payments from week six to week eight remained at an income replacement of 100% or DM 600[15] if the mother was previously unemployed. Between three and six months, maternity benefits declined from DM 750[13] to DM 600[15] per month. From the seventh month to the 10^{th} month (and later 12^{th} month), the amount of maternity benefits was means tested and depended on the family income during the two years prior to childbirth. Around 84% of individuals were eligible for the full amount

[11] The summary of the parental leave reforms through 1985 are mainly based on Zmarzlik et al. (1999). For the later reforms later see Bundeserziehungsgeldgesetz [BErzGG] [Federal Child-Raising Benefit Act], Dec. 6, 1985, BGBl.I at 2154 (F.R.G.) and its changes through its abolition in 2007.

[12] Minor reforms more precisely specified the conditions under which mothers are exempted and thus allowed to work during this period.

[13] This is equivalent to $ 758 in 2017.

[14] Additionally, paternity leave was introduced. However, between 1987 and 1994 only around an average of 1% of fathers took parental leave (Vaskovics & Rost, 1999).

[15] This is equivalent to $ 606 in 2017.

of the benefits (Schoenberg & Ludsteck, 2014). I summarize these conditions to form policy regime I, which provides one full year of employment protection and maternity benefits.

Table 1: Parental Leave Reforms from 1986 until 2006

	Month, Year	**Job Prot.**	**Maternity Benefits**
Regime I	January, 1986	10 months	3-6 months DM 600,[15] 7-10 months means tested
	January, 1988	12 months	up to 12 months
Regime II	July, 1989	15 months	up to 15 months
	July, 1990	18 months	up to 18 months
Regime III	January, 1992	36 months	up to 18 months
	January, 1993		up to 24 months
	January, 2007	maternal benefits are related to previous earnings	

A further increase in the employment protection and maximum maternity benefit duration from 12 months to 15 months took effect in July 1989 and another rise to 18 months in July 1990. These reforms are summarized in regime II, which provides 1.5 years of employment protection and maternity benefits. In January 1992, the employment protection period was further extended to a total of three years. In contrast, the maximum maternity payment period initially remained constant at 18 months, before being extended to two years in January 1993. Minor changes in family policy were introduced in 2001, but the core regime of 1993 still continued.[16] This forms regime III, which provides 3 years of employment protection and 2 years of maternity benefits. Before a major reform was introduced in 2007, the policies did not noticeably change. The 2007 reform then changed the maternity benefits to become a replacement of the pre-birth income.

[16]There was a minor change in the maternity benefits in 1994. For the first six months benefits were also means tested. For married couples, the threshold was DM $100,000$, for singles DM $75,000$ for getting the full benefits in the first six months.

3 Data

In my estimations, I use longitudinal data from the German Socio-Economic Panel Study (SOEP) covering years 1986 through 2006 (see Wagner et al., 2007, for a description of the SOEP).[17] Starting in 1984, the SOEP interviewed private households and persons in Germany. Annually, all household members older than 16 are interviewed on a yearly basis, condition on their voluntary collaboration. New additions to a household, including partners and children, also remain in the sample, even after leaving the household. The original SOEP sample was expanded with several booster samples over the years. The questionnaires cover a wide range of topics, including details on demographics, education, labor market dynamics, earnings, and other income, among others.

While the SOEP interviews individuals on a yearly basis, it asks participants to fill out a monthly calendar of the previous year. In particular, individuals are asked about last year's employment history. This allows me to construct a semi-annual data set by combining the current year's questionnaire with information from the questionnaire of the following year. A particularly useful feature is that the SOEP has a possible option "maternity leave" for the monthly employment state. That previously employed mothers consistently use this option emphasizes that the employment protection is a well-known and well-understood policy to mothers. The SOEP also asks newly surveyed individuals, older than 16, to fill out a specific questionnaire collecting information about their life before they were included in the sample. This enables me to collect information on each individual's age when finishing their education and starting their work life.

I restrict the sample to women and, when applicable, their partners between the age of 18 and 50.[18] Because some reforms took place before the reunification of Germany, I exclude individuals living in East Germany. Self-employed individuals are not influenced by the reforms, because they do not have an employer who has to guarantee them their job for a given period. In contrast, individuals working in the public sector might have additional employment protection, which might even be longer than three years.[19] Both groups are therefore excluded from the sample. [20]

Some further data cleaning and labeling is worth pointing out. The labor market experience for a given year is constructed by combining the answers of a working history questionnaire and the recorded employment state of follow up interviews. Part-time and full-time experience are sep-

[17] I also use the wave corresponding to 2007, since it includes responses addressing 2006.

[18] For estimations for some exogenous processes, I include women until the age of 70 in order to have more robust estimates for the later years.

[19] Note that to qualify for the more generous maternity leave conditions in the public sectors, individuals must to have been employed regularly in this sector directly before having their child. Therefore, mothers are not able to receive these more generous conditions when switching sectors *after* having had their child.

[20] For similar reasons, women who are subject to least one of the following criteria are also not included in the sample: living outside Germany, being severely disabled, or having at least one multiple birth. Missing information on the age of their children, their labor market entry age, or their labor market experience also leads to exclusion.

arately measured. Wages are defined as gross monthly earnings divided by actual working hours during the same period. The model does not include any macro economic processes, therefore all money values are deflated using the Consumer Price Index and the base year 2000 (Federal Reserve Bank of St. Louis, 2016). To reduce the importance of measurement error in wages, the wage distribution is trimmed at the fourth and 98^{th} percentiles, from below and above, respectively.[21]

The resulting data set is an unbalanced panel in which individuals enter and leave the panel at various ages. In total there are 4,670 women. More than 53 % of these are observed for more than 5 years, about 19 % for more than 10 years. Additionally, I observe 1,750 births and a total of 3,465 children aged 18 or younger. In total the sample has 57,585 semi-annual observations. Table 2 shows the distribution of family types for various age and education levels. Low education indicates that the individuals do not have a university degree after finishing education, while high education indicates that individuals have at least a bachelor degree.[22] The table shows that single mothers are rather an exception. Higher educated women tend to have their children later in life and have fewer children than women with lower education.

Table 2: Distribution of family types at different ages

	Mothers		Non Mothers		Number of
	Singles	In Couples	Singles	In Couples	Observations
			Women aged 25		
Low education	0.04	0.38	0.24	0.33	937
High education	0.01	0.26	0.36	0.35	79
			Women aged 30		
Low education	0.06	0.65	0.09	0.20	925
High education	0.02	0.42	0.17	0.38	178
			Women aged 35		
Low education	0.08	0.75	0.06	0.11	923
High education	0.03	0.62	0.10	0.23	201

Finally, since the identification exploits the different maternity leave regimes, an overview of the number of observations in the three regimes is helpful. It is provided in table 3. Although the

[21] After trimming, the lowest hourly wage is € 4.21 and the highest wage is € 25.72.

[22] The low number of observations for women with at least a bachelor degree at age 25 is a result of some women having not yet finished education at this age. The distribution of the labor force entry ages depending on education can be found in appendix B.1

SOEP is a survey and regime II was only in place for 2.5 years, I observe 127 distinct women with a child under the age of 3 for the second regime. For these women, $1,138$ labor supply decisions are recorded. For the other regimes, there are more observations. For regime I and III, I observe 404 and $1,037$, respectively. They make $1,568$ and $7,718$ labor supply choices.

Table 3: Observations per regime

	women	decisions
Regime I	404	1568
Regime II	127	1138
Regime III	1037	7718

Notes: Column 1 represents the number of women observed in the respective regime who have a child under the age of 3. Column 2 represents the number of decisions observed for these women.

4 Suggestive evidence for overconfidence

An indicator for overconfidence with regards to future employment prospects is present when individuals systematically underestimate the time they need to find new employment. One of the SOEP questions tries to collect evidence of this sort. Since 199, it is collected every second year. All non-employed subjects who answered on a previous question that they seek employment in the future, are requested to indicate the probability of future life events, including the likelihood of being in employment within the next two years.[23] Knowing the date of the interview, it is possible to track individuals for whom a response is recorded and investigate if they found employment within the two years. Comparing the average stated probability and the average of individuals having found employment provides suggestive evidence for biased expectations. As table 4 shows, there is indeed a gap between the average stated likelihood and the average realization of the same group of individuals.[24]

The first column shows the average stated likelihood and the average actual realization of the whole sample. Columns two to five list the values for women who stated a likelihood of being in employment within the next two years of at least 30 %, 50 %, 80 % and 100 %, respectively. To list

[23]For the exact questions, see appendix A.1

[24]See also Kassenboehmer & Schatz (2017) who find similar results in a sample including men.

values of these groups seems important, since Kassenboehmer & Schatz (2017) show that low stated probabilities are primarily driven by individuals who are long-term unemployed and lost faith in their ability finding employment. The group of interest in this paper, mothers with employment protection, most likely does not belong to this group, since they currently have the opportunity to return to their previous job.

In table 4, the average stated probability is provided in row 1, the actual realization of the same individuals in row 2. Row 3 states by how much individuals overestimate their chances to find employment within two years. Row 4 provides the p-value of the difference between row 1 and 2, and the last row the number of observations for each respective group. The critique of Manski (1990) that standard expectation data is not well equipped to investigate the question of rational expectations does not apply in this case, since individuals are explicitly asked to state the probability using a Likert-type scale with a range of 11 values. Manski's critique is mostly applicable to questions with binary answers, since these are more challenging for estimating underlying probabilities.[25]

Table 4: Employment Expectations vs. Realizations

	Average	**Stated** $>= 30$	**Stated** $>= 50$	**Stated** $>= 80$	**Stated** $= 100$
Stated	45.89 %	66.35 %	72.78 %	92.66 %	100.00 %
Actual	36.79 %	46.01 %	49.04 %	58.43 %	68.17 %
Overest.	24.73 %	44.21 %	48.41 %	58.58 %	46.69 %
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	1294	848	696	345	192

Notes: Row 1 represents the stated probability to be in employment within the next two years, row 2 states the real percentage of individuals having found employment within two years, row 3 shows by how much individuals overestimated the probability on average, row 4 denotes the p-value of the hypothesis that there is no difference between row 1 and row 2 and row 5 shows the number of observations. The original question reads as follows: "How likely is it that you start paid work within the next two years?" Only subjects who stated that they want to work in the future are asked. The answers are recorded on an 11-point Likert-type scale from 0 to 100 percent. Individuals for whom I can neither observe the length of their unemployment spell nor that they were unemployed for more than two years are excluded. Survey weights are used.

[25] The Likert-type scale has the range 0% to 100% in 10 percentage points steps. In the worst case, under rational expectations, individuals would estimate their likelihood only slightly above the median between two points on the scale and, thus, always choose the higher value. Hence, a deviation below 5% does not necessarily provide enough evidence to reject the null hypothesis of rational expectations. Even when subtracting 5% off all stated likelihoods, the differences stated in table 4 are still significant at the 1% level.

In addition, the data is collected between 1999 and 2006, a period during which Germany's unemployment rate did not fluctuate much, staying between 9 % and 12 % percent. Two years in which the question about future employment expectations was asked were followed by a decline in the unemployment rate, while the other two years were followed by a recession.[26] Thus, it is plausible to assume that the differences in expectations and realizations are not driven by aggregate shocks.

The table unveils two important aspects. First, it shows that individuals, on average, overestimate the likelihood of finding employment within the next two years by 25 %. The gap widens almost monotonically with higher predicted likelihoods to find employment. For individuals who stated a probability over 50 %, the average prediction is about 73 %, but in reality only 49 % find employment within two years, causing an overestimation of about 48 %. Second, expectations are not random, as there is a positive correlation between stated preferences and realizations. It seems that individuals can, to a certain degree, predict their likelihood in relation to others, but on average systematically overestimate the likelihood of finding employment.

5 Model

Although, there is some suggestive evidence showing that women indeed exhibit overconfidence in future employment possibilities, the descriptive analysis does not allow for quantify the costs of this overconfidence as it remains unclear how much it contributes to lengthy career breaks related to childbirth. Additionally, estimating effects of potential policy reforms aiming at reducing the career cost of overconfidence is challenging in a reduced form approach. The discrete choice dynamic life cycle model developed in this section aims to address these issues. It has major similarities to the model in Blundell et al. (2016).[27]

5.1 Outline of the model

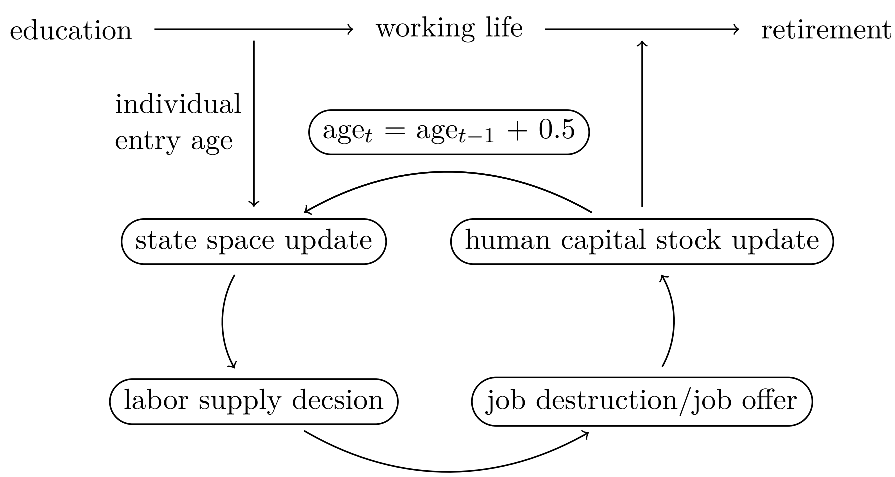
Figure 1 provides an overview of the general life cycle process of the model. The main focus is on the working life of females between the ages of 18 and 50. Because the labor market entry age might even differ substantially between individuals with same education degrees, the model might start at a different age for individuals with the same educational attainment.

As figure 1 shows, after finishing education and entering working life, all women enter the life cycle element of the model. Each period lasts for one half year and begins with the determination

[26] For a detailed overview of the unemployment rate during the time of the interviews see appendix A.2

[27] The major difference is that the model developed here includes labor market frictions. On the contrary, saving decisions are not explicitly modeled. There is a long history for these kind of dynamic life cycle models of labor supply, see for example Heckman & Macurdy (1980), Eckstein & Wolpin (1989), Van der Klaauw (1996), Attanasio et al. (2008) and Adda et al. (2017).

Figure 1: Outline of the model



of the variables that influence the labor supply decision. This includes the forming and termination of partnerships, the birth of children, and the realization of taste shocks. Similar to Blundell et al. (2016), partnerships and children are not modeled as explicit choices, but as exogenous stochastic processes. Since the forming and termination of partnerships depends on the characteristics of the women, including education, age and current family state, the model includes assortative matching similar to the observed data. When individuals maximize their expected lifetime utility, they account for the possibilities of partnerships and children.[28]

After the state space for the current period is set, each woman chooses the number of hours she wants to supply for the current period. The possible supplied hours are discretized into three categories, non-employment (0 hours per week), part-time employment (20 hours per week), and full-time employment (40 hours per week). The realization of the hours choice depends on the labor market and the woman's previous employment state. If a woman was not employed in the previous period, she needs to receive a job offer if she desires to work in the current period. If a woman was employed in the previous period, she might lose her employment involuntary due to plant closure or other external factors. In this case, she can work neither full-time nor part-time in the current period and must await the next period for possible reemployment.

An important feature of the model is that women hold expectations about the probability of receiving a job offer in a future period. These expectations are not limited to align with the true job offer probabilities. Individuals are allowed to systematically under- or over-estimate these. In contrast, all other probabilities, for instance the ones about partnerships and children are restricted

[28]in order to reduce the computational burden of the estimation, partnerships and children are not modeled as actual choices. There is a long history of modeling partners and children in this way, see for example Van der Klaauw (1996), Sheran (2007) and Blundell et al. (2016).

to align with the true probabilities.

At the end of each period, the on-the-job human capital stock is updated. It is a crucial factor for determining the wage that an individual woman can realize on the labor market. When entering the labor market, individuals do not have any on-the-job human capital, since it is only gained through employment. Similar to Blundell et al. (2016), full-time employment lets the human capital stock grow with a potential different rate than part-time employment. Being non-employed depreciates the on-the-job human capital stock. After the human capital stock update, the period ends and a new periods starts. The outlined process repeats until the age of 50, which is the last period of the model.

5.2 The structural model

This subsection provides further details about the functional form assumptions. Individuals must make a labor supply decision (l_t) each period, depending on their characteristics after entering the working life stage of the model. The characteristics include the age (t), education (s), on the job human capital (e_t), the employment state of the last period (l_{t-1}), the presence of a partner (p_t), the presence of children (cd_t), age of the youngest child (ac_t), current policy regime (r_t), and the employment protection state (jp_t). In principle, they can choose between non-employment ($l_t = NE$), part-time employment ($l_t = PT$), and full-time employment ($l_t = FT$).[29]

Flow utility. The instantaneous utility of a choice depends on its consumption possibility and its leisure time. Consumption and the utility from leisure are allowed to vary with the presence of a partner, the presence of children, and the age of the youngest child. I assume that utility is separable over time, but the instantaneous utility is non separable between consumption and leisure. The functional form is given by

$$u_{i,t} = \frac{(c_{i,t}/\bar{c}_{eq} - 1)^{(1-\gamma_c)} - 1}{1 - \gamma_C} \times U^L\left(l_{i,t}, s_{i,t}, p_{i,t}, cd_{i,t}, ac_{i,t}\right) + \varepsilon_{i,t} \tag{1}$$

where $c_{i,t}$ denotes the consumption and $\bar{c}$ an equivalence scale[30] that controls for the members of the household. $U^L(\cdot)$ represents the utility from leisure varying with education and family demographics. It is normalized to 1 if the woman does not work. The CRRA-parameter γ_c represents the risk aversion. Finally, the choice specific shock $\varepsilon_{i,t}$ is independently and identically distributed over time and labor supply choices with a type-1 extreme value distribution with zero-mean. The utility

[29] I assume 260 paid working days in a given year, which equals 130 working days in a half-year. Part-time employment is standardized to be 20 working hours in a week (520 hours a half-year), full-time employment to be 40 working hours in a week (1040 working hours a half-year). Both hour values are the median hours worked in the sample, when subjects stated that they are working part-time or full-time, respectively.

[30] I assume that $\bar{c} = 1$ for single women without children, $\bar{c} = 1.4$ for single mothers, $\bar{c} = 1.6$ for couples without children, and $\bar{c} = 2$ for couples with children.

of leisure is normalized to 1 if the individual is not working in the current period. The leisure preferences vary with working hours and education, and additional depend on the presence of a partner and children. As given in equation (2), the utility derived from leisure differs with the age of the youngest child, in a quadratic manner.

$$
\begin{aligned}
U^L\left(l_{i,t}, s_{i,t}, p_{i,t}, cd_{i,t}, ac_{i,t}\right) = & \sum_{l' \in \{PT,FT\}} \sum_{s' \in \{low,high\}} \gamma_{l',s'} \mathbb{1}_{[l_{i,t}=l', s_{i,t}=s', cd_{i,t}=0]} \\
& + \sum_{l' \in \{PT,FT\}} \sum_{s' \in \{low,high\}} \gamma_{l',s',p} \mathbb{1}_{[l_{i,t}=l', s_{i,t}=s', p_{i,t}=1]} \\
& + \sum_{l' \in \{PT,FT\}} \mathbb{1}_{[l_{i,t}=l', cd_{i,t}=1]} \left(\gamma_{l',ac_0} + \gamma_{l',ac_1} ac_{i,t} + \gamma_{l',ac_1} ac_{i,t}^2\right)
\end{aligned}
\tag{2}
$$

Wages and Human Capital. The decision to work and the resulting hours choice depend on the possible consumption opportunities of the choice. Income from employment is driven by the following wage process:

$$
\begin{aligned}
\ln(w_{i,t}) = & \ln(\gamma_{w,low}) \mathbb{1}_{\{s=low\}} + \ln(\gamma_{w,high}) \mathbb{1}_{\{s=high\}} \\
& + \gamma_{w,s,e} \ln(e_{i,t} + 1) + \xi_{i,t}
\end{aligned}
\tag{3}
$$

The hourly wage rate depends on the individual's highest education degree and accumulated on-the-job human capital. $\xi_{i,t}$ is to be assumed a measurement error that follows a normal distribution with standard deviation σ_ξ. Since the education does not change over the life cycle in the model, wage differences over time are driven by on-the-job human capital. It evolves in the following manner:

$$
e_{i,t} = \begin{cases} e_{i,t-1}(1-\eta_s) & \text{if } l_{i,t-1} = NE \\ e_{i,t-1}(1-\eta_s) + \lambda_s & \text{if } l_{i,t-1} = PT \\ e_{i,t-1}(1-\eta_s) + 0.5 & \text{if } l_{i,t-1} = FT \end{cases}
\tag{4}
$$

Human capital at the end of each period depends on the previous period's human capital and the employment state of the current period. In each period, the on-the-job human capital depreciates with the rate $(1-\eta)$.[31] Accumulation depends on the working hours with potentially different gains for part-time and full-time employment. Being in a model with a semi-annual decision period, the gain of full-time employment is normalized to be 0.5. The gain from part-time employment is estimated in order to not restrict the model to a specific ratio in wage growth between the two employment states. All parameters of the human capital process are education specific.

Budget Constraint. Given the labor supply decision and the wage process, consumption is

[31] At the start of the working life, every individual is assumed to not have any on-the-job human capital.

determined by:

$$
\begin{aligned}
c_{i,t}(l_{i,t}, p_{i,t}, ac_{i,t}) = 520 \times \Big(w_{i,t} - \mathbb{1}_{\{cd_{i,t}\}} cc(ac_{i,t})\Big) \times (2 \times \mathbb{1}_{\{l_{i,t}=FT\}} + \mathbb{1}_{\{l_{i,t}=PT\}}) \\
+ \mathbb{1}_{\{p_{i,t}\}} earn^{p}_{i,t} \\
- TT(earn^{w}_{i,t}, earn^{p}_{i,t}, cd_{i,t}, ac_{i,t})
\end{aligned} \tag{5}
$$

where $earn^{w}_{i,t}$ and $earn^{p}_{i,t}$ stand for the gross labor earnings of the woman and her partner, respectively. The function $cc(\cdot)$ stands for the childcare costs, which are taken from the data and depend on the age of the youngest child.[32] For each hour that the woman works, she needs childcare for children under the age of 6. $TT(\cdot)$ represents the German tax and transfer system. I model all key features of the German tax and transfer system. In particular, joint taxation, unemployment benefits, social assistance and childcare benefits are modeled carefully, since they might strongly affect the financial incentives to work.

Job offers and expectations. Women face labor market frictions when seeking employment. To work a positive number of hours after a period of non-employment, women must receive a job offer. The probability of receiving such an offer depends on her education and is denoted by $\pi^{O}(l_{t-1}, s)$. It is possible that the agents of the model systematically over- or underestimate this offer probability. I assume that individuals do not update their expected job offer rate over time.[33] With $\widetilde{\pi}^{O}(l_{t-1}, s)$ standing for the expected job offer rate, the following relation between the expected and the true job offer rate is given:

$$
\begin{aligned}
&\widetilde{\pi}^{O}(l_{t-1}, s) = \alpha\, \pi^{O}(l_{t-1}, s) \\
\text{where} \qquad &\alpha \in [0, \frac{1}{\pi^{O}(l_{t-1}, s)}]
\end{aligned} \tag{6}
$$

The parameter α determines the degree of deviation from the true job offer rate. It can never fall below zero, since this would result in an expected job offer rate below 0. Similarly α must not exceed the inverse of the true job offer arrival rate, since individuals would expect the job offer arrival rate to be greater than one. Depending on the size of α the individuals might have rational expectations, underestimate or overestimate the true job offer rate:

$$
\begin{aligned}
\text{rational expectations if } \alpha = 1 \\
\text{underestimation if } \alpha < 1 \\
\text{overestimation if } \alpha > 1
\end{aligned} \tag{7}
$$

[32] I follow the approach of Wrohlich (2011) by including individuals without positive childcare costs when computing the average expected childcare costs. One hour of care costs €1.82 for children under the age of 3 and €1.15 for children between the age of 3 and 6.

[33] Due to the rare event of being non-employed and then re-entering employment, it seems plausible that individuals do not have many opportunities to learn about the real job offer rate over the life cycle.

The nesting of rational expectations in the model allows for a straightforward testing of the hypothesis of non-biased expectations, by testing if $\alpha = 1$ after the estimation.

Job loss. When employed in the previous period, a woman can also involuntary loose her employment. Provided the woman worked in the previous period, there is an exogenous probability that the plant closes, denoted in the model by $\pi^L(l_{t-1})$. In this case, she is not able to choose employment in the current period, but must wait for a job offer in the next period if she wants to re-enter employment. This probability is estimated outside the model using information provided in the SOEP sample. Whenever an individual leaves employment, she is asked for the particular reason. The questionnaire offers voluntary separation, plant closure, and layoffs, among others as possible answers.

Family dynamics. The birth of children, along with the formation and termination of partnerships, are modeled as exogenous stochastic processes depending on the woman's education, age, and current family demographics. The probability of having a first child differs from the probability of additional children.[34] In the model, and in line with Blundell et al. (2016), only the age of the youngest child affects leisure preferences and costs, thus whenever a new child is born, the age of the youngest child is reset to zero. Children live in the household until they turn 18. Beginning a new partnership depends only on age and education, while separations also depend on the presence of children and the age of the youngest child. This approach captures the assortative matching present in the partnership market. Partners contribute to the household consumption and influence the women's leisure preferences. To keep the computational burden manageable, the partners' earnings are modeled to depend on the characteristics of the woman, including her age, education, and family state.[35] Agents in the model know about these probabilities and accommodate for these when forming expectations about future periods.

5.3 Maximizing expected lifetime utility

Given the preferences, the labor market frictions, and the external processes, women maximize their expected lifetime utility each period. In a given period t, this utility is formally given by

$$\max_{\{l_t, l_{t+1}, \ldots, l_T\}} V_t(l_t, l_{t+1}, \ldots, l_T, \omega_t) = u(l_t, \omega_t) + \mathbb{E}\left[\sum_{\tau=t+1}^{T} \beta^{\tau-t} u(l_\tau, \omega_\tau) \middle| \omega_t \right] \tag{8}$$

where the index of i is dropped for the ease of notation. The parameter β represents the discount factor, $\mathbb{E}[\cdot]$ the expectation operator, and ω_t a realization of the state space Ω_t in period t. The

[34] Since the model's decision period is a half-year, women are not able to have an additional child if the youngest child has not reached the age of one.

[35] This approach is similar to Van der Klaauw (1996), Sheran (2007) and Adda et al. (2017).

state space is defined as

$$\Omega_t = \{s, e_t, l_{t-1}, cd_t, ac_t, p_t, jp_{t-1}, r_t\}$$

Having specified the lifetime utility, and assuming the separability between the choice-specific error term and the rest of the utility function, the model can be represented in a two period decision process characterized by the Bellman (1957) equations (9) and (10).

$$\begin{aligned}
&\text{for } t < T: \\
&\quad v_t(l_t = NE, \omega_t) \\
&\qquad = u^*(l_t, \omega_t) + \varepsilon_{l_t,t} \\
&\qquad\quad + \beta \sum_{\substack{\omega_{t+1} \\ \in \Omega_{t+1}}} \Bigg\{ \widetilde{\pi}^O(s) \mathbb{E}\left[\max_{j \in L} \{ v^*_{t+1}(j, \omega_{t+1}) + \varepsilon_{j,t+1} \} \middle| \widetilde{\pi}^O(s) \right] \\
&\qquad\qquad + \left(1 - \widetilde{\pi}^O(s)\right) \mathbb{E}\left[v^*_{t+1}(NE, \omega_{t+1}) + \varepsilon_{NE,t+1} \right] \Bigg\} q(\omega_{t+1} | l_t, \omega_t) \\
&\quad v_t(l_t \in \{PT, FT\},\ \omega_t) \\
&\qquad = u^*(l_t, \omega_t) + \varepsilon_{l_t,t} \\
&\qquad\quad + \beta \sum_{\substack{\omega_{t+1} \\ \in \Omega_{t+1}}} \Bigg\{ \left(1 - \pi^L\right) \mathbb{E}\left[\max_{j \in L} \{ v^*_{t+1}(j, \omega_{t+1}) + \varepsilon_{j,t+1} \} \middle| \pi^L \right] \\
&\qquad\qquad + \pi^L \mathbb{E}\left[v^*_{t+1}(NE, \omega_{t+1}) + \varepsilon_{NE,t+1} \right] \Bigg\} q(\omega_{t+1} | l_t, \omega_t)
\end{aligned} \tag{9}$$

$$\begin{aligned}
&\text{for } t = T: \\
&\quad v_t(l_T, \omega_T) = u^*(l_T, \omega_T) + \varepsilon_{l_T,T}
\end{aligned} \tag{10}$$

where $q(\omega_{t+1}|l_t, \omega_t)$ denotes the probability of arriving at state space ω_{t+1} given choice l_t and state space ω_t, and $u^*_{i,t}$ the utility function without the choice specific error term, i.e. $u^*_{i,t} \equiv u_{i,t} - \varepsilon_{i,t}$. Similarly, $v(\cdot)^* \equiv v(l_t, \omega_t) - \varepsilon_{l_t,t}$ denotes the value function without the choice specific error term. Note that the expected value functions are choice specific, since the probability to choose from all three alternatives in a subsequent period depends on the current period's choice. Further, only the biased expectations about the future job arrival rates enter the value function, since they represent what the individual expects in the future.

Two assumptions help with the formulation of the stated value functions. First, I assume that individuals do not know that their expected job offer probability might differ from the actual offer rate and, second, they also do not update their expected job offer probability over the life cycle. This causes individuals to treat the expected employment probability as given when maximizing their expected lifetime utility. As a result, there is no correlation between the expected job offer rate and the expected choice specific error component. Additionally, I assume that mothers fully understand the institutional settings and know that they receive employment protection when they qualify for it. Thus mothers in employment protection do not have a bias about their possible choice restriction in the next period. They correctly assume they can return to employment, less the probability of a plant closure, during that time. Since the model has a finite horizon, it can be solved by backwards induction using equations (9) and (10) for a given set of parameters.

6 Identification and Structural Estimation

Although section 4 provides some suggestive evidence that individuals might overestimate their probability of finding employment, the evidence is based on a stated preferences approach. In contrast, the revealed preferences approach presented in this section relies only on actual choices. Both approaches have their advantages and disadvantages,[36] but employing both creates a stronger case when collecting evidence for overconfidence and its resulting costs. For the discussion of the identification, some simplification in the notation is helpful. By assuming that $\varepsilon_{j,t}$ is type-I extreme value distributed with zero mean, equation (9) can be rewritten as

$$\begin{aligned} v_t(l_t = NE, \omega_t) &= u(l_t, \omega_t) \\ &+ \beta \sum_{\substack{\omega_{t+1} \\ \in \Omega_{t+1}}} \left\{ \widetilde{\pi}^O(s) \ln \left(\sum_{j \in L} \exp(v^*_{t+1}(j, \omega_{t+1})) \right) \right. \\ &\qquad \left. + \left(1 - \widetilde{\pi}^O(s)\right) v^*_{t+1}(NE, \omega_{t+1}) \right\} q(\omega_{t+1} | l_t, \omega_t) \\ v_t(l_t \in PT, FT, \omega_t) &= u(l_t, \omega_t) \\ &+ \beta \sum_{\substack{\omega_{t+1} \\ \in \Omega_{t+1}}} \left\{ \left(1 - \pi^L\right) \ln \left(\sum_{j \in L} \exp(v^*_{t+1}(j, \omega_{t+1})) \right) \right. \\ &\qquad \left. + \pi^L v^*_{t+1}(NE, \omega_{t+1}) \right\} q(\omega_{t+1} | l_t, \omega_t). \end{aligned} \tag{11}$$

[36]The major difference between both methods in this paper is that the stated preference approach relies on a single question for which individuals do not face any consequences when answering it non truthfully, while the revealed preference approach is based on actual choices in the real world. There are several reasons why the suggestive evidence should be interpreted with care. First, individuals might answer strategically, thinking their answers might influence policy choices. Second, the framing and the precise wording of the question might influence subjects differently, resulting in a wide variety of possible interpretations of their answers. Third, the concept of probabilities might be challenging for a significant number of subjects, thus preventing some individuals from answering the question correctly (see for example Tversky & Kahneman, 1973). Although the labor market state is recorded via the same survey, and thus also potentially prone to the same problem, the question refers to already made choices and is much easier to interpret. Also, strategically answering the question about past employment states seems to be less reasonable.

To reduce the space of some equations, I additionally use the following expressions:

$$
\begin{aligned}
E \in & \{PT, FT\} \\
LS(E, \omega_{t+1}) = & \ln\left(\sum_{j \in L} \exp(v^*_{t+1}(j, \omega_{t+1}))\right) \\
LS(NE, \omega_{t+1}) = & v^*_{t+1}(NE, \omega_{t+1})) \\
\Delta LS(E - NE, \omega_{t+1}) = & LS(E, \omega_{t+1}) - LS(NE, \omega_{t+1}))
\end{aligned}
\tag{12}
$$

6.1 Identification

The identification of the model combines a bunching related approach, exploiting a discontinuity in the future expected value of non-employment, with exogenous variation from three major maternity leave reforms. The bunching caused by the discontinuity primarily identifies the expectations about the future job offer rate. The reforms create counterfactual-like situations, such that it is possible to evaluate behavior in the absence of the discontinuity. This approach allows for separate identification of the real job offer arrival rates, the expectation about these rates and the individuals' preferences. The section starts with an overview of the identification strategy to provide intuition on how observed choices identify the model's key parameters. Afterwards, a more formal discussion is presented.

6.1.1 Overview of Identification Strategy

Identifying Expectations. The end of employment protection introduces a discontinuity in the probability to be able to choose employment in subsequent periods. During the protection, mothers can freely decide if they want to return to part-time or full-time employment, or if they want to remain non-employed, since they are guaranteed their previous job by law. The only risk they are facing is that their plant might close and thus they lose their employment guarantee. If their career break lasts beyond the end of the protection period, the likelihood to be restricted in future choices changes, since they need to rely on a job offer to choose part-time or full-time employment in this situation. The discontinuity at the end of the protection lets mothers, who in a world without labor market frictions would choose to have lengthy career breaks, consider returning earlier, taking advantage of real employment protection. Stated differently, some mothers return within the employment protection period because it is harder to find employment once the protection ends.

The lower a mother estimates her probability of being restricted in her next period's choice, that is the higher she expects the job arrival rate to be, the less likely she is to return within the last period of employment protection. Thus, the number of returning mothers right before the end of employment protection informs about the average expectations of the future job offer probability. Herby, an important aspect is that this decision to return within the employment protection is made when the mothers have not yet faced real labor market frictions, but only can hold expectations about these.

Equations (13) and (14) illustrate what changes in the future expected value function in the period before the employment protection ends. Both equations show the trade-off between the future value of employment and non-employment conditioned on the mother not having re-entered employment since giving birth. Equation (13) depicts the situation of an individual enjoying employment protection for at least the next period, while equation (14) depicts the situation in which there is no future employment protection. In equation (13), the correct $\pi^O(s)$ is known to the individual and equals one minus the probability of a job loss, since the mother enjoys employment protection and is fully aware of it. Note that the probability to be able to choose from the entire choice set is the same, independent of choosing re-entering employment or staying non-employed. In equation (14), and thus in the last period of employment protection, this changes. When choosing to be non-employed in the current period, but desiring to work in the next period, an individual has to rely on a job offer. In contrast, choosing to be employed in the current period, only restricts the choice set with the probability of a plant closure.

Employment protection in the next period:

$$\begin{aligned}
[v_t(NE_t,\omega_t)-&u(NE_t,\omega_t)] - [v_t(E_t,\omega_t) - u(E_t,\omega_t)] = \\
&\beta \sum_{\substack{\omega_{t+1} \\ \in\Omega_{t+1}}} \left\{\left(1-\pi^L\right)\Delta LS(E-NE,\omega_{t+1}) + LS(NE,\omega_{t+1})\right\} q(\omega_{t+1}|NE_t,\omega_t) \\
&-\beta \sum_{\substack{\omega_{t+1} \\ \in\Omega_{t+1}}} \left\{\left(1-\pi^L\right)\Delta LS(E-NE,\omega_{t+1}) + LS(NE,\omega_{t+1})\right\} q(\omega_{t+1}|E_t,\omega_t)
\end{aligned} \tag{13}$$

No employment protection in the next period:

$$\begin{aligned}
[v_t(NE_t,\omega_t)-&u(NE_t,\omega_t)] - [v_t(E_t,\omega_t) - u(E_t,\omega_t)] = \\
&\beta \sum_{\substack{\omega_{t+1} \\ \in\Omega_{t+1}}} \left\{\widetilde{\pi}(NE,s)\Delta LS(E-NE,\omega_{t+1}) + LS(NE,\omega_{t+1})\right\} q(\omega_{t+1}|NE_t,\omega_t) \\
&-\beta \sum_{\substack{\omega_{t+1} \\ \in\Omega_{t+1}}} \left\{\left(1-\pi^L\right)\Delta LS(E-NE,\omega_{t+1}) + LS(NE,\omega_{t+1})\right\} q(\omega_{t+1}|E_t,\omega_t)
\end{aligned} \tag{14}$$

Therefore, even if the current utility of being non-employed far exceeds the current utility of being employed, the woman might still choose employment due to its higher future value.[37] The

[37] Note that as long as there is some utility in choosing employment, the expected maximum of being able to choose between employment and non-employment is always greater than the expected maximum of only being able to choose non-employment.

higher that the difference in the future values are, the more probable the choice of re-entering employment in the last period of the employment protection becomes and, thus, more individuals return to employment in this last period. The difference in the future values depends strongly on the expected job offer rate. The higher this expected job offer rate is, the less severe is the difference in the future values and the less bunching should be observed at the end of the protection period. In fact, if individuals expect the job offer rate as high as $(1 - \pi^L)$, there is no discontinuity at all and, thus, there should be no observable difference between the returning rate shortly before the end of employment protection and shortly after the end of employment protection.

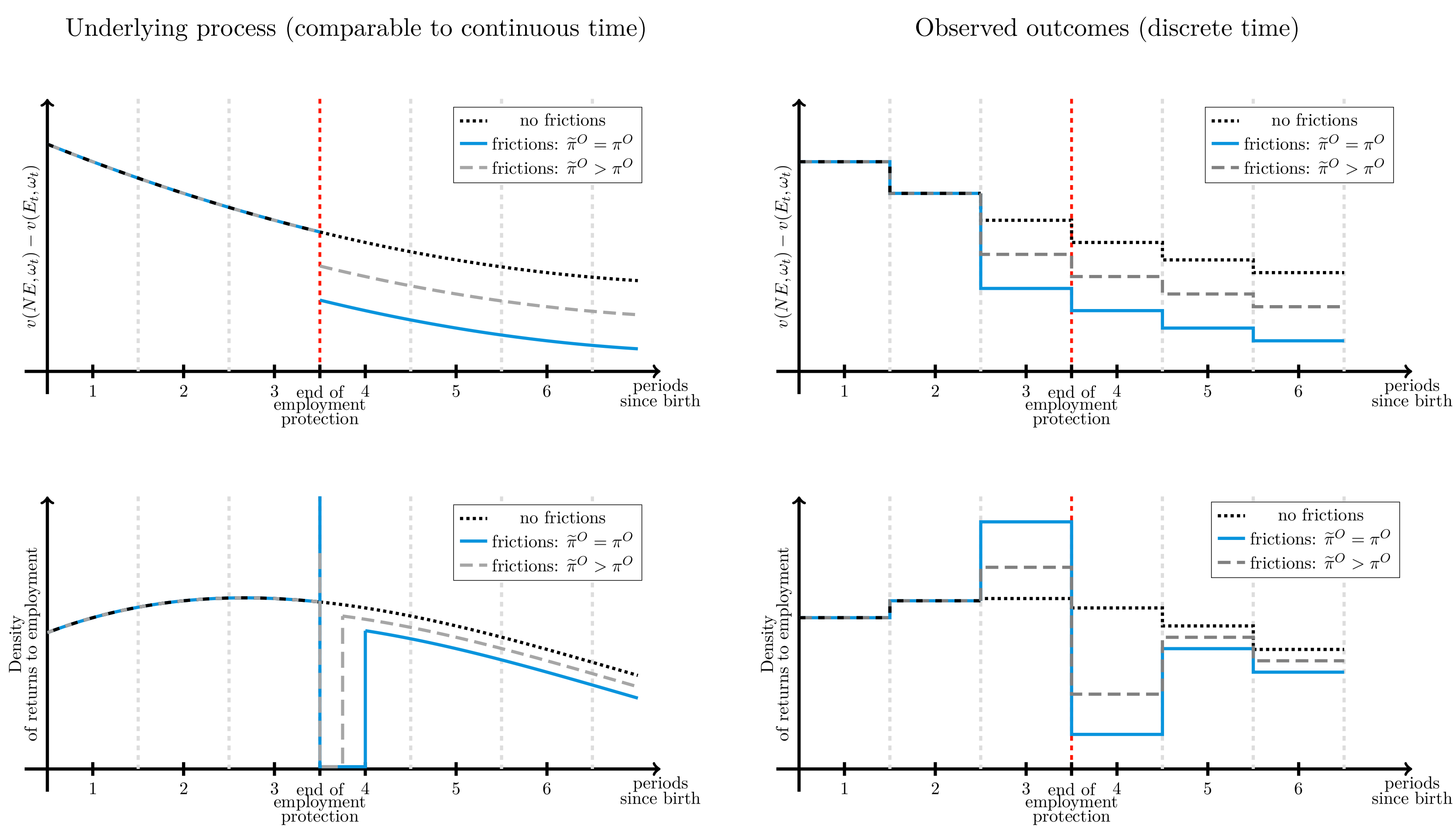
Figure 2 visualizes the identification of the job offer expectations. The left panel of the figure illustrates the underlying process. It is comparable to a model with continuous time. The right panel depicts the difference in the value functions and the observed outcomes when time is discrete. The side-by-side placement provides a better understanding of the translation from the underlying preferences (top left panel) to the observed outcomes in the data (bottom right panel). All x-axes denote the time since the birth of the youngest child. The employment protection is assumed to end with period three. The top graphs plot the difference in the value functions between non-employment and employment, while the bottom graphs show the density of mothers returning to employment at a given time.[38]

Three scenarios are depicted. The first scenario, depicted by the dotted black Line, represents the counterfactual situation when the employment protection does not end with period 3. It equals the scenario in which individuals expect the job offer rate to be exactly as high as the probability of not losing employment due to a plant closure. The second scenario, depicted by the solid blue line, graphs a situation in which individuals have rational expectations about their future employment possibilities. The third scenario depicted by the dashed gray line represents individuals with biased expectations. They are overestimating the probability of finding employment after the end of the employment protection. However, they anticipate that the probability is lower than in the protection period and therefore differ from the individuals in scenario I.

To identify the expected job offer rate, the discontinuity in the value function is pivotal. As seen by the three scenarios, the more optimistic that the individuals are about their future employment prospects, the lower is the bunching of returnees at the end of the employment protection. In the underlying process, the majority of women would return to employment immediately before

[38] As the plot indicates, the graph assumes that, in the absence of the end of employment protection, the difference between the value of non-employment and employment shrinks over time. This is mainly due to the shrinking utility of leisure as the child gets older. Additionally, the more the human capital depreciates while not working, the smaller the difference between the future values of non-employment and employment gets. In the graph, it is assumed that the first effect is more dominant than the second. That the density is not monotonically increasing in the bottom figures is due to the assumption that the majority of individuals are assumed to have returned before the end of period 3.

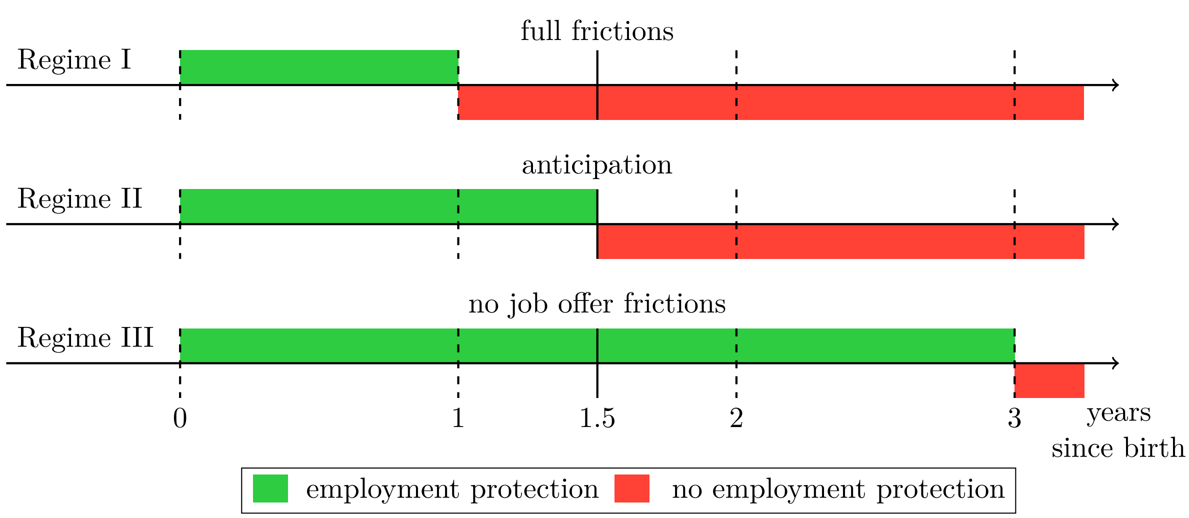
Figure 2: Identification of Expectations



the end of the employment protection, while in the discrete data, the majority returns in the last period of the employment protection, spanning over more time. It is important that the decision to return within the employment protection is made before actually facing the labor market frictions. Therefore, the individual can only have expectations about the job offer probability. This reinforces that the excess mass at the end of the employment protection is strongly influenced by future expectations about these frictions.

Separating Expectations from Preferences and Real Job Offer Rates. In principle, the bunching of returnees at the end of the employment protection can stem from other discontinuities in the value function. For example, if individuals' utility derived from leisure in regard to the age of the youngest child discontinuously changes at the end of period 3, the lower graphs of figure 2 would look similar. To separate discontinuities in preferences from discontinuities in the expected future value function, it is necessary to know the counterfactual scenario in which the employment protection goes beyond the third period. Furthermore, the identification of the real job offer rate can be archived by comparing choices of individuals facing labor market frictions and individuals who do not. The maternity leave regimes presented in section 2 provide such counterfactual scenarios. Figure 3 visualizes the time lines of the regimes. It shows all three regimes and their respective lengths of employment protection depending on the years since childbirth. The green bar on top of a regime's timeline indicate that the individual's jobs are still protected, while in contrast the red bars below indicate that the individual has to receive a job offer if she desires to re-enter employment.

Figure 3: Identification Policy Reforms



The different durations of employment protection by the three regimes creates, exogenously, three groups each facing different environments when the youngest child reaches the age of 1.5 years. In regime II, mothers face the end of the employment protection. Thus, the number of people returning to employment in the period before their youngest child turns 1.5 in regime II contributes to the identification of job offer expectations. Mothers in employment protection in regime III do not have to worry about job offer rates until their youngest child reaches the age of 3. Therefore, the number of returning mothers shortly before their youngest child exceeds the age of 1.5, can be used to control for other discontinuities in preferences at this age. Finally, the transition rates of mothers in regime I, when their youngest child reaches the age of 1.5, can be used for identification of the real job offer rate.[39]

The transition probabilities from non-employment to employment of women in employment protection in regime 3 can be used to identify leisure preferences depending on the age of the youngest child. As demonstrated by equation (13), the difference in future value functions is only generated by the different transition probabilities of the state space $q(\omega_{t+1}|NE_t, \omega_t) \neq q(\omega_{t+1}|E_t, \omega_t)$. The only difference for the transition probabilities is the human capital stock, which results in a higher future wage when choosing employment. Assume that the consumption preferences are identified,[40] then it is in principle possible to quantify the differences in the future expected values of non-employment and employment, since these differences are only related to consumption. In a dynamic discrete choice model like the one presented here, the differences in the overall value functions are identified by the observed choice probabilities of individuals with the respective state values (see for example Hotz & Miller, 1993). Therefore, given the differences in the value functions, it is possible to identify the differences in instantaneous utility functions of working and not working from the respective choice probabilities. This difference informs about the leisure preferences.

The true job offer rate can be recovered by comparing the transition rates of non-employed individuals in regime 1 with the ones from regime 3 for the periods in which individuals face different employment protection states in the regimes. The transitions of the individuals in regime 3 for this time period are not affected by the labor market frictions, while, in contrast, individuals from regime 1 are. The difference informs about how restricted individuals are in their choice set when they are non-employed.

6.1.2 Formal Identification

After having provided intuition for identification, this subsection shows how the key parameters are formally identified.[41] The fundamental identification strategy relies on comparisons of observ-

[39]Note that regime III and regime II also function as counterfactual scenarios for regime I, and regime I functions in addition to regime II as a counterfactual scenario for regime III.

[40]Appendix D shows how these preferences are formally identified.

[41]It is important to note that the parameters are estimated together using the method of simulated moments. For this method, all parameter estimates can be influenced by all moments. Thus there is no *exclusive* matching of individual moments to respective parameters as the following discussion might suggest. Nevertheless, the derived moments are potentially the most influential for the respective parameter.

able choice probabilities. Without loss of generality, most of the discussion abstracts from choices in working hours and considers only the decision between employment (E) and non-employment (NE). Occasionally, the state space is split into $\Omega_t^- = \Omega_t \setminus x_{t-1}$ and x_{t-1}, meaning that x_{t-1} is excluded from the state space and listed separately. For example, I denote observed choice probabilities as $\Pr(l_t|l_{t-1}, \omega_t^-, jp_t)$ describing choice l_t, conditioning on the individual's choice l_{t-1} last period and this period's state space ω_t^- and employment protection state jp_t.[42] Similarly, $v(l_t, \omega_t^-, jp_t)$ denotes the value function of choice l_t, given the state space ω_t^- and the employment protection state jp_t.

Since the conditional observed choice probabilities are crucial in the identification of the model, the discussion starts with the general choice probabilities, followed by the choice probabilities when individuals enjoy employment protection. Given the model, the probability to choose employment, conditioned on being employed in the previous period, is the product of the unconditional choice probability and the probability of not losing a job:

$$\begin{aligned}\Pr\left(E|E, \omega_t^-, jp_t = 0\right) &= \left(1 - \pi^L\right) \Pr\left(\varepsilon_{NE,t+1} < v^*(E, \omega_t) + \varepsilon_{E,t+1} - v^*(NE, \omega_t)\right) \\ &= \left(1 - \pi^L\right) \frac{\exp\left(v^*(E, \omega_t)\right)}{\sum\limits_{j \in L} \exp\left(v^*(j, \omega_t)\right)}\end{aligned} \tag{15}$$

The probability of being employed if the individual was not employed in the previous period is the product of the unconditional choice probability and the probability of receiving a job offer:

$$\begin{aligned}\Pr\left(E|NE, \omega_t^-, jp_t = 0\right) =& \pi^O(\omega_t) \Pr\left(\varepsilon_{NE,t+1} < v^*(E, \omega_t) + \varepsilon_{E,t+1} - v^*(NE, \omega_t)\right) \\ =& \pi^O(\omega_t) \frac{\exp\left(v^*(E, \omega_t)\right)}{\sum\limits_{j \in L} \exp\left(v^*(j, \omega_t)\right)}\end{aligned} \tag{16}$$

The observed choice probabilities are based on the true job offer probability, since this is the probability that ultimately determines if a woman has received a real job offer. The biased job offer expectations only occur indirectly in the value functions of equations (15) and (16).

The main difference between an individual who enjoys employment protection and an individual who does not is the need to receive a job offer when wanting to be employed. Similar to an employed individual, women with employment protection carry the risk of a plant closure or comparable involuntary separations. The probability to observe an individual in employment while in

[42] Being in employment protection is then indicated by 1, while not being in employment protection by 0.

employment protection is

$$\Pr\left(E|NE,\omega_t^-,jp_t=1\right) = \Pr\left(\varepsilon_{E,t+1} < v^*(E,\omega_t) + \varepsilon_{E,t+1} - v^*(NE,\omega_t)\right)$$
$$=(1-\pi^L)\frac{\exp\left(v^*(E,\omega_t)\right)}{\sum\limits_{j\in L}\exp\left(v^*(j,\omega_t)\right)}. \tag{17}$$

The probabilities of choosing non-employment is not discussed separately, since these are the complementary probabilities of the above stated probabilities and, therefore, do not provide new information for identification.

Identification of the True Job Offer Probability. To identify the real job offer probabilities, the observed choice probabilities of individuals with the same state space, besides last periods employment state are compared. The value function of both types of individuals are the same, since last period's employment state only affects the probability to be able to choose employment:

$$\frac{\Pr\left(E|NE,\omega_t^-,jp_t=0\right)}{\Pr(E|E,\omega_t^-,jp_t=0)} = \frac{\exp\left(v^*(E,\omega_t)\right)}{\sum\limits_{j\in L}\exp\left(v^*(j,\omega_t)\right)}\pi^O(\omega_t)\frac{\sum\limits_{j\in L}\exp\left(v^*(j,\omega_t)\right)}{(1-\pi^L)\exp\left(v^*(E,\omega_t)\right)} \tag{18}$$

Since the data provides direct information on the separation rate π^L, it is possible to treat it as known. Therefore, equation (19) identifies the job offer probability and it is assumed to be known for the rest of the paper.

$$\frac{\Pr\left(E|NE,\omega_t\right)\left(1-\pi^L\right)}{\Pr\left(E|E,\omega_t\right)} = \pi^O(\omega_t) \tag{19}$$

The important assumption for identification is that observed employment to employment transitions are, besides preferences, only influenced by the risk of an involuntary separation. In the model, employment to employment transitions include individuals who stay in their previous jobs as well as individuals who change directly from one job to another without a period of non-employment. In addition to the above, the differences in transitions from non-employment to employment between mothers who enjoy employment protection and mothers who do not due to the different policy regimes, identifies the job offer rates. It is burdensome to show this analytically, since the future expected value functions between these two groups also differ when employment protection lasts into the future.[43]

Identification of Expected Job Offer Probability. The formal identification of expecta-

[43]In contrast to equation (18), if individuals differ also in their expected future values ($v(\cdot)$), terms do not easily cancel out. Still, if groups only differ in employment protection status, different job arrival rates have a different effect on the observed choice probabilities. This allows linking the ratio of their choice probabilities to the job arrival rates and, thus, identifies these rates in addition to the presented moments.

tions of the job arrival rate uses two regimes and does not rely on the functional forms of the utility function and wage process. The crucial part for the identification of expectations is the end of the employment protection and its resulting discontinuity in future expected values. Using the observed choice probabilities of a group of individuals from regime I, who are no longer fertile,[44] but their youngest child has reached the age of 1, the difference in future expected values can be derived. The starting point to obtain this difference is the expected logarithm of the ratio between the choice probabilities of employment and non-employment net the probability of a job loss. For individuals in regime I, who are in employment protection, this is

Regime I:

$$\begin{aligned}
&\mathbb{E}LR_{RI}(\omega_t^-, ac_t = 1, jp_t = 1, r = I) \\
&\qquad = \mathbb{E}\left[\ln\left(\frac{\Pr(E|NE, \omega_t^-, ac = 1)}{\Pr(NE|NE, \omega_t^-, ac = 1) - \pi^L} \right) \right] \\
&\qquad = \mathbb{E}\Bigg[u(E, \omega_t^-, ac = 1) - u(NE, \omega_t^-, ac = 1) \\
&\qquad\qquad + \beta \sum_{\omega_{t+1}} \left\{ (1 - \pi^L) LS(E, \omega_{t+1}^-, ac = 1.5) + \pi^L LS(NE, \omega_{t+1}^-, ac = 1.5) \right\} \\
&\qquad\qquad\qquad q(\omega_{t+1}^-, ac = 1.5 | E, \omega_t^-, ac = 1) \\
&\qquad\qquad - \beta \sum_{\omega_{t+1}} \left\{ \widetilde{\pi}^O(\omega_t) LS(E, \omega_{t+1}^-, ac = 1.5) + (1 - \widetilde{\pi}^O(\omega_t)) LS(NE, \omega_{t+1}^-, ac = 1.5) \right\} \\
&\qquad\qquad\qquad q(\omega_{t+1}^-, ac = 1.5 | NE, \omega_t^-, ac = 1) \Bigg]
\end{aligned} \tag{20}$$

where the $\mathbb{E}LR_{RI}(\omega_t^-, ac = 1)$ is introduced in order to simplify notation by denoting the expected logarithm of the choice probabilities. Since the women are in their last period of employment protection, staying non-employed in the current period causes them to rely on a future job offer if they desired to re-enter employment then. In contrast, women from regime II, can remain non-employed for another period, before they have to rely on job arrivals. Their difference in the expected future value functions is:

Regime II:

[44] Assuming that there are no future children simplifies the formal discussion, but is not necessary to identify expectations.

$$
\begin{aligned}
&\mathbb{E}LR_{RII}(\omega_t^-, ac_t = 1, jp_t = 1, r_t = II) \\
&\qquad = \mathbb{E}\left[\ln\left(\frac{\Pr(E|NE, \omega_t^-, ac = 1)}{\Pr(NE|NE, \omega_t^-, ac = 1) - \pi^L}\right)\right] \\
&\qquad = \mathbb{E}\Bigg[u(E, \omega_t^-, ac = 1) - u(NE, \omega_t^-, ac = 1) \\
&\qquad\qquad + \beta \sum_{\omega_{t+1}} \Big\{(1-\pi^L)LS(E, \omega_{t+1}^-, ac = 1.5) + \pi^L LS(NE, \omega_{t+1}^-, ac = 1.5)\Big\} \\
&\qquad\qquad\qquad q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1) \\
&\qquad\qquad - \beta \sum_{\omega_{t+1}} \Big\{(1-\pi^L)LS(E, \omega_{t+1}^-, ac = 1.5) + \pi^L LS(NE, \omega_{t+1}^-, ac = 1.5)\Big\} \\
&\qquad\qquad\qquad q(\omega_{t+1}^-, ac = 1.5|NE, \omega_t^-, ac = 1)\Bigg]
\end{aligned} \tag{21}
$$

By subtracting (20) from (21), it is possible to eliminate the current choice utilities, such that only the difference in the future choices is left:[45]

$$
\begin{aligned}
\mathbb{E}LR_{RI}(\omega_t^-, ac = 1) - &\mathbb{E}LR_{RII}(\omega_t^-, ac = 1) \\
= &\beta \sum_{\omega_{t+1}} \Big\{\widetilde{\pi}^O(\omega_t)\Delta LS(E - NE, \omega_{t+1}^-, ac = 1.5)\Big\} \\
&\qquad q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1.0) \\
&- \beta \sum_{\omega_{t+1}} \Big\{(1-\pi^L)\Delta LS(E - NE, \omega_{t+1}^-, ac = 1.5)\Big\} \\
&\qquad q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1.0) \\
= &\beta \sum_{\omega_{t+1}} \Big\{\Big[\widetilde{\pi}^O(\omega_t) - (1-\pi^L)\Big]\Delta LS(E - NE, \omega_{t+1}^-, ac = 1.5)\Big\} \\
&\qquad q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1.0)
\end{aligned} \tag{22}
$$

$\mathbb{E}LR_{RI}(\omega_t^-, ac = 1)$ and $\mathbb{E}LR_{RII}(\omega_t^-, ac = 1)$ are computed from the observed choice probabilities. Similarly, the transition probabilities $q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1.0)$[46] and the rate of involuntary job separations π^L can also be recovered directly from the data. In addition $\Delta LS(E - NE, \omega_{t+1})$

[45]Note that this assumes that there are no financial differences between being non-employed and enjoying employment protection and being non-employed without the protection. This simplifies the formal identification argumentation. Since maternity benefits are means tested in the regimes, this refers to groups that do not qualify for these benefits. Identification comes also from individuals receiving maternity benefits since the structural model and estimation can account for differences in incomes, once consumption preferences are identified.

[46]This is achived by observing the probability from transitioning from a given choice and state space to another state space.

for all $\omega_{t+1} \in \Omega_t$ can be computed by using choice probabilities and the real job arrival rate:

$$\begin{aligned}
\Delta LS(E - NE, \omega_{t+1}) =& \ln\left(\sum_j \exp(v(j, \omega_{t+1}))\right) - \ln\left(\exp(v(NE, \omega_{t+1}))\right) \\
=& \ln\left(\frac{\sum_j \exp(v(j, \omega_{t+1}))}{\exp(v(NE, \omega_{t+1}))}\right) \\
=& \frac{\pi^O(\omega_t)}{\Pr(NE|E, \omega_t) - (1 - \pi^O(\omega_t))}
\end{aligned} \tag{23}$$

This allows to rewrite equation (22) as

$$\begin{aligned}
\mathbb{E}LR_{RI}(\omega_t^-, ac = 1) - & \mathbb{E}LR_{RII}(\omega_t^-, ac = 1) \\
=& \beta \sum_{\omega_{t+1}} \left\{ \frac{\left[\widetilde{\pi}^O(\omega_t) - (1 - \pi^L)\right] \pi^O(\omega_t)}{\Pr(NE|E, \omega_t) - (1 - \pi^O(\omega_t))} \right\} q(\omega_{t+1}^-, ac = 1.5|E, \omega_t^-, ac = 1)
\end{aligned} \tag{24}$$

Equation (24) identifies $\widetilde{\pi}^O(\omega_t)$, since it is the only parameters not known in the equation.[47] Since the expected and the real job offer rate are connect via the parameter α, that parameter is also identified, since both probabilities are identified:

$$\alpha = \frac{\pi^O(\omega_t)}{\widetilde{\pi}^O(\omega_t)} \tag{25}$$

6.2 Estimation Procedure

The estimation procedure is divided into two parts. In a first step, the exogenous processes and parameters are estimated. These include the forming and ending of partnerships, the arrival of children, the probability of involuntary job separation,[48] and the childcare costs. Furthermore, the semi-annual discount factor β is set to $\sqrt{0.98}$, the square root of the annual discount factor found, for example, in Blundell et al. (2016) and Attanasio et al. (2008). Two studies employing similar utility functions, which allow for non-separability of leisure and consumption.[49] In the second step, relying on the parameters estimated in the first step, a method of moments estimation is carried out to recover the structural parameters of the model.

As the identification section describes, most moments consists of conditional choice probabilities and transition rates. Only for identification of the wage process, are wage related averages and

[47]In principle, it is possible to identify β in this particular setting, as shown by Haan et al. (2017). However, in this estimation, the parameter is set to a typical value found in the literature.

[48]Each individual who transitions out of employment is asked for the particular reason. Among the choices are, for example, plant closures or other forms of lay-offs besides the possibility to answer with an individual reason.

[49]Haan & Prowse (2017) use the same discount factor in an estimation based on SOEP data.

their trajectories used. To identify the job offer expectations, moments depending on the age of the youngest child of all three regimes are used. The algorithm of the estimation of the second step is as follows:

1. For a given set of parameters (Θ), the described model is solved via backwards induction.

2. Given the choice-specific value functions, all life cycle decisions for all observed women are simulated. For each woman in the sample, ten life cycles are simulated.

3. All periods in the simulated data that are not observed in the SOEP data for a respective woman are deleted.[50] Step 1 and 2 result in a simulated data set with exactly ten times as many observations as in the observed data.

4. For the simulated and the observed sample all moments are computed and the value of the following objective function is computed:

$$f(\Theta) = \left\{ \sum_{k=1}^{K} \left[\left(M_k^d - \frac{1}{s} \sum_{s=1}^{10} M_k^s(\Theta) \right)^2 / \ \mathbb{V}\mathrm{ar} \left(M_k^d \right) \right] \right\} \tag{26}$$

   where K is the number of moments, M_k^d denotes the k-th data moment, and M_k^s the k-th simulated data moments using data from replication s.

5. Given the value of the objective function, the algorithm then chooses new parameters.

6. Steps 1 - 5 are repeated until $\hat{\Theta} = \arg\min_{\Theta} f(\Theta)$ is found.

Note that I do not use the asymptotically optimal weighting matrix, because of its poor small sample properties (see Altonji & Segal, 1996). Instead, as equation (26) illustrates, I use a diagonal matrix that has on its diagonal the sample variances of the respective moments. This variance is estimated using bootstrapping with clustering at the individual level.[51] The method of simulated moments tries to maximize the similarity between the simulated data and the observed data, where similarity refers to the chosen moments.

To estimate the standard errors of Θ, I use the formula provided by Gourieroux et al. (1993). Since the simulated choices are discrete outcomes, the objective function is a step function and does not possess valid derivatives at all points. Therefore, a derivative-free optimization routine is used that generates in each iteration a quadratic approximation of the objective function, which it then

[50] Furthermore, wages are only recorded when the simulated individual is employed and the original SOEP interview took place at the given period. To account for non-random missing wages, a linear probability model is used to fit the probability of not observing a wage given the state space variables. Simulated wages are then deleted according to this probability.

[51] I use 1499 replications following Davidson & MacKinnon (2000).

optimizes. This method is also known as bound optimization by quadratic approximation and is implemented here using the Dakota toolkit (see Adams et al., 2013).

7 Empirical Results

At the moment, only a reduced version of the presented model is estimated. Besides the discounting parameter, the CRRA parameter is set to 2, a value typical found in the literature. Furthermore, the model does not include unobservable heterogeneity and wage errors. Table 5 shows the estimated parameters for the utility function, table 6 for the wage and human capital process and table 7 for the labor market frictions and the ratio to the expectations.

Table 5: Utility Function

Parameter	low education	high education
$\gamma_{Part-Time}$	-1.3107	-0.2684
$\gamma_{Full-Time}$	1.0339	2.7350
$\gamma_{Part-Time,\, Partner}$	-0.5367	-1.8442
$\gamma_{Full-Time,\, Partner}$	0.1906	-1.3894
	part-time	full-time
$\gamma_{children,\, constant}$	-1.431760	-2.400033
$\gamma_{children,linear}$	0.166683	-0.068743
$\gamma_{children\ ,quadratic}$	0.1129	0.1283

Table 6: Wage and Human Capital Parameters

Parameter	low education	high education
$\gamma_{wage,\, constant}$	7.5681	12.2948
$\gamma_{wage,\, e}$	0.1570	0.02735
$\gamma_{wage,\, eta}$	0.0035063	0.000005
$\gamma_{wage,\, \lambda}$	0.2512	0.2490

Table 7: Job Offer

Parameter	low education	high education
Job Offer Prob. (half-yearly)	0.0711	0.1149
α	2.2471	

The parameters of the job offers are particularly interesting. Receiving a job offer in a given half-year is rather rare, with a probability of 7,1% for low educated women and 11.5% for high educated. These values are reasonable when compared to the average employment finding rate of table 4. Transforming the average rate of finding employment within two years to a half-yearly job arrival rate results in 10.83%, a value between the two estimates.[52] In addition, Haan & Prowse (2017) find similar values using a SOEP sample that also includes men. The value for the parameter α also aligns with the suggestive evidence of section 4. If the two-year rates are transformed to half-yearly values, the average α is about 1.3137. But as mentioned earlier, this value is driven by long-term unemployed people, who have lost faith in finding new employment. For the groups with higher expectations in table 4, the half-yearly α lies between 1.67 and 4.02.[53]

7.1 Goodness of fit

Figures 4, 5, and 6 show the fit of the model. While the real data is presented in solid lines, the simulation of the model with the estimated parameters is shown in dashed lines. All graphs display individuals with low education in black and individuals with high education in gray. Although the model does not include age specific parameters besides the family formation, the life cycle employment rates are well reflected by the simulated model. For older ages, the model slightly overestimates the share of individuals working full-time, while it underestimates the share of individuals working part-time. The model represents the labor supply decision after the birth of a child especially well, as shown in figure 5.

7.2 Overconfidence vs. rational Expectations

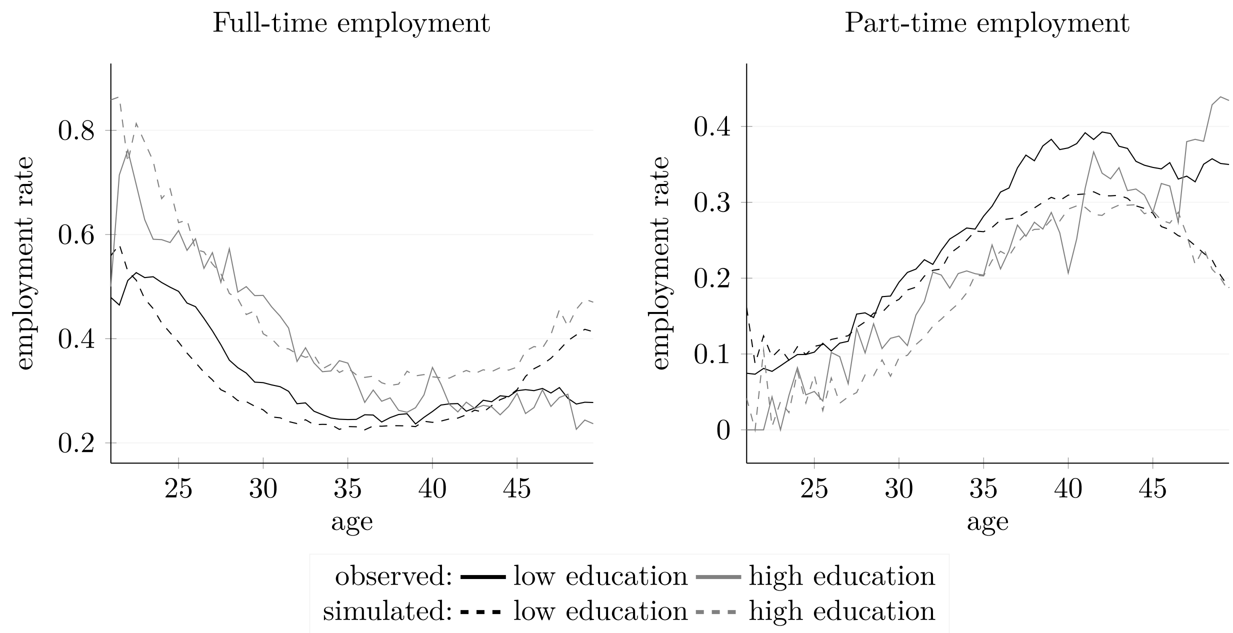
Using the estimated parameters, it is possible to quantify the consequences of overconfidence. To do so, I randomly draw 10,000 individuals from my sample and simulate their life cycle decisions, once with biased expectations and once with rational expectations, holding everything else constant. The results are striking. When employment protection lasts for a year (regime I), overconfidence prolongs career breaks on average by 11 months, if the protection lasts for one and a half year (regime II), the career break is prolonged by 9 months, and if the protection last for three years (regime III), by 7 months.

To quantify the costs, I compute the net present values of all earnings from employment at the individual's labor force entry age. These values are computed once for the estimated parameters

[52] The easiest way to compute this probability is to take 100% minus the chance of not finding employment within 4 half-years and solving for the half-yearly job offer rate: $1-(1-\pi^O)^4 = 0.3679$.

[53] For the group that states a probability greater than or equal to 30% for finding employment within two years, the half-yearly α equals 1.67, for the group stating the probability greater than or equal to 50%, it is 1.79, for the group stating the probability greater than or equal to 80% it is 2.43 and for the group that is sure to find employment within the next two years it is 4.02.

Figure 4: Employment Rates by Age

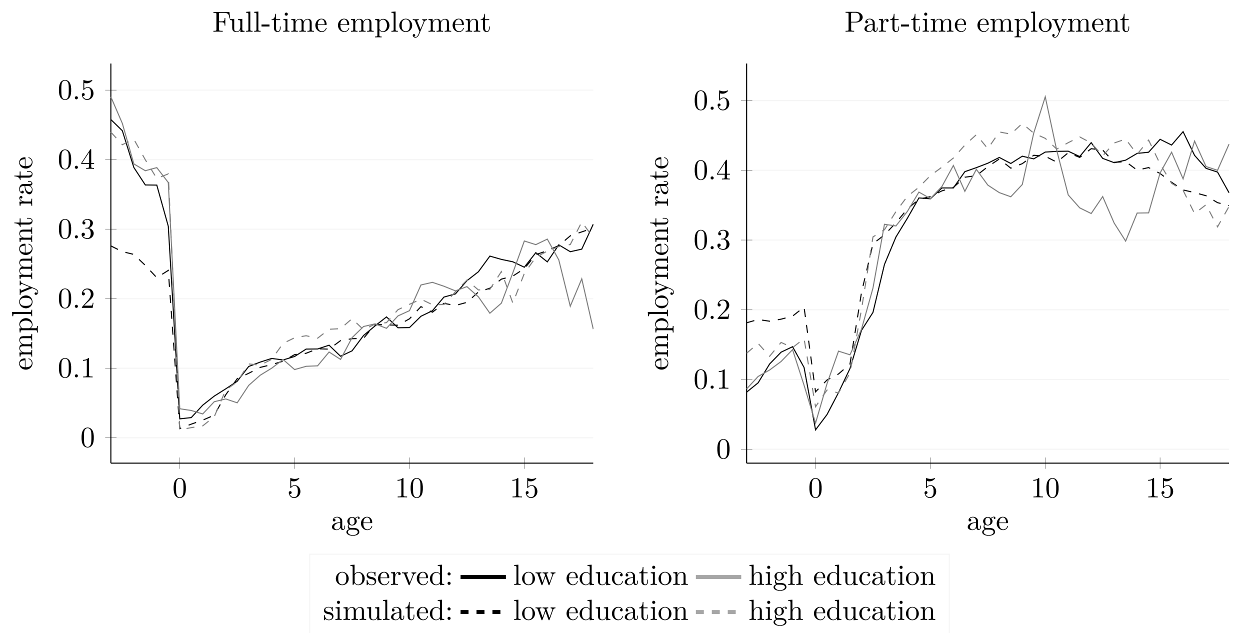


Notes: Comparison of the observed and simulated female employment rates over the life cycle. Observed rates are in solid lines and are based on the SOEP data. Simulated rates are in dashed lines and are based on the estimated model. Black lines represent the group of individuals who do not have some college education, while gray lines represent the group having received at least some college.

and once for a model that restricts individuals to exhibit rational expectations. For regime I, the net present value is 17% lower, when individuals are overconfident. For regime II, it is 15% and for regime III, 13% lower. The differences in the net present values of household consumption are much smaller with 4.0% for regime I, 3.6% for regime II, and 3.1% for regime III.

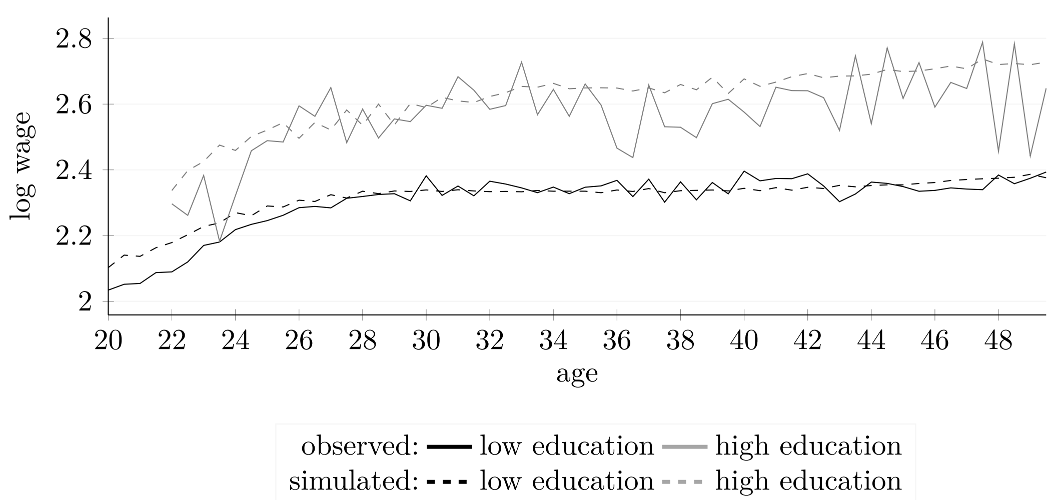
There are several reasons for the differences between the net present value of earnings from employment and household consumption. First, earnings from employment do not include any unemployment or maternity leave benefits, while these are included in the household consumption. Second, most mothers live in a partnership in which the husband contributes the majority of the household earnings. The large majority of mothers, once they return to employment decide to work part-time, as shown in figure 5, while their partners usually stay in full-time employment. This automatically generates large differences in the contribution to the household consumption. Third, at the core of the German tax system is the joint taxation of couples, which heavily taxes the secondary earner income. Thus the net consumption differences between non-working and working are much smaller than the differences in the gross earnings.

Figure 5: Employment rates by time to/since childbirth



Notes: Comparison of the observed and simulated female employment rates by time to/since childbirth. Observed rates based on SOEP data are in solid lines. Simulated rates estimated from the model are in dashed lines. Black lines represent individuals without college education, gray lines represent individuals with at least some college education.

Figure 6: Mean log wage rates over the life cycle



Notes: Comparison of the observed and simulated log wages over the life cycle. Observed log wages are in solid lines. Log wages simulated from the model are in dashed lines. Black lines represent individuals without college education, gray lines represent individuals with at least some college education.

8 Conclusion

The birth of children strongly influences the working careers of women, especially since a majority of mothers remain at home for an extended period of time before re-entering employment. The length of this career break is strongly influenced by the expectations about future employment possibilities. Overconfidence in being able to find new employment may lead a share of mothers to stay at home beyond the end of the employment protection offered in many countries, although sub-optimal with rational expectations. This causes losses in earnings and human capital.

I develop a structural life cycle model of female labor supply and human capital accumulation, allowing for non-rational expectations of future job arrival rates. To identify expectations within the model, I derive a novel identification strategy that allows recovering the key parameters from observed labor supply choices. The strategy exploits a discontinuity in the future expected value of non-employment caused by the end of an employment protection. In combination with maternity leave reforms that change the duration of the employment protection after the birth of a child, it is possible to separately identify each of expectations, job-arrival rates and preferences. I estimate the model using survey data from the German Socio-Economic Panel Study, since the German setting provides the necessary variation for identification.

Estimations show that mothers indeed highly overestimate their chances on the labor market, since they expect the half-yearly job arrival rate to be twice the actual rate on average. Simulations with the estimated preference parameters, but restricted to rational expectations, show that overconfidence prolongs career breaks on average for about eight months. This results in a reduction of lifetime earnings from employment between 13% and 17%. However, due to the typically stronger contribution of the husband to the household earnings and the German joint taxation, system which heavily taxes the secondary earner, overconfidence reduces the lifetime household consumption by around 3.3% on average.

The results have important implications from a public economics perspective. Prolonged career breaks increase social security spending and the life-time losses in earnings from employment translate directly into forgone tax revenue. The consequences for the individual are also substantial. The income loss causes reduced pension benefits, thus, contributing to an increased risk of poverty in retirement. Since biased expectations can be interpreted as market failures and because of their far-reaching consequences, interventions by the policy maker might be justified. Possible policies aim on providing better information about the labor market conditions, for example by sending official information letters to new families, or financial incentives to return within the period the individual's job is protected.

Overall, some caution is appropriate when interpreting these results, since the model only estimates an average bias for all individuals and does not model an explicit retirement decision. Adding heterogeneity in expectations might be valuable, since individuals most likely exhibit different degrees of overconfidence causing different magnitudes of career costs. While heterogeneity based on observables can be estimated using the presented strategy, including unobservable heterogeneity demands a strong refinement of the identification approach. Extending the model by including a retirement decision presumably results in an increase in the costs of overconfidence, since the lost earnings from employment result in a lower average pension income. However, it is not immediately evident if individuals will postpone their retirement to overcome these losses. In future work, I plan to incorporate these elements into the model and to simulate the effects of possible policies, aiming to reduce the cost of overconfidence. These can for example be an increase in in-work benefits conditioned on returning within the employment protection or further prolonging employment protection without prolonging maternity benefits.

Appendix A: Suggestive Evidence: Additional Information

Appendix A.1 SOEP Questions

The suggestive evidence of section 4 is based on the following two SOEP questions. Only individuals who respond (b), (c), or (d) in the first question are asked the second question.

Do you intend to engage in paid employment (again) in the future?

(a) No, definitely not

(b) Probably not

(c) Probably

(d) Yes, definitely

The original questionnaire also underlines the words "next two years" in the following question.

How likely is it that one or more of the following occupational changes will take place in your life within the <u>next two years</u>?

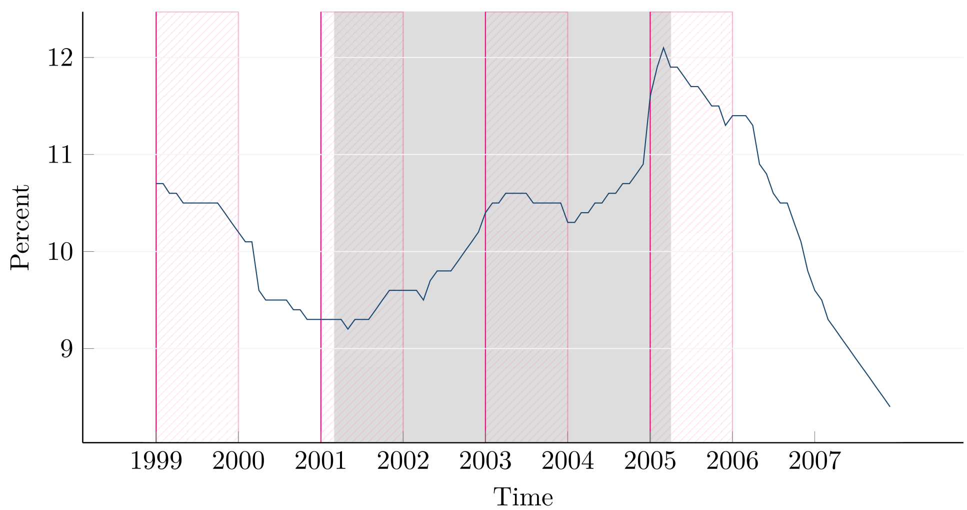
Start paid work	☐ 0	☐ 10	☐ 20	☐ 30	☐ 40	☐ 50	☐ 60	☐ 70	☐ 80	☐ 90	☐ 100
Become self-employed	☐ 0	☐ 10	☐ 20	☐ 30	☐ 40	☐ 50	☐ 60	☐ 70	☐ 80	☐ 90	☐ 100
Receive further education	☐ 0	☐ 10	☐ 20	☐ 30	☐ 40	☐ 50	☐ 60	☐ 70	☐ 80	☐ 90	☐ 100

Appendix A.2 Registered Unemployment Rate for Germany between 1999 and 2007

A possible explanation for a gap between the stated likelihood to find employment and the realizations is that individuals were affected by a shared macro shock. If the economy falls into an unexpected recession, it is harder for everyone to find employment and, thus, it is natural to expect a gap between stated preferences and realizations. Figure 7 shows that this is unlikely to drive the results in section 4. It plots the unemployment rate for the relevant years of table 4. The questions were first asked in 1999 and then again in 2001, 2003, and 2005. Although the SOEP interview can happen at any time throughout the year, the majority are in spring. The possible interview times are indicated by the shaded pink areas in the figure. The gray area marks a recession according to the definition of the OECD.

Overall the unemployment rate did not fluctuate much, staying between 8.4% and 12.1%. Two years when the question was asked are then followed by a recession, while the other two years are followed by a drop in the unemployment rate. Overall, this should at least partly balance the macro influence on the realizations.

Figure 7: Registered Unemployment Rate for Germany



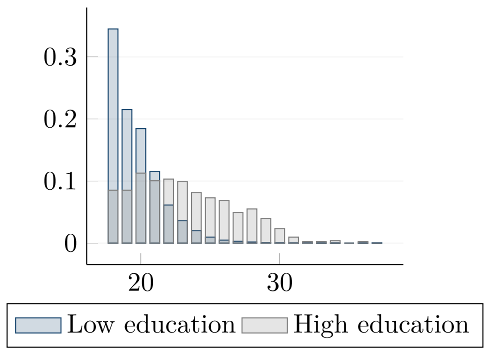
Notes: The blue line depicts the monthly registered unemployment rate in Germany. The gray area marks recessions by definition of the OECD. The shaded pink areas indicate the year over which subjects were asked about their employment expectations. Sources: Federal Reserve Bank of St. Louis (2017a), Federal Reserve Bank of St. Louis (2017b).

Appendix B: Additional Descriptive Statistics

Appendix B.1 Labor force entry age distribution

Since the model only distinguishes between high and low education, individuals within these groups enter their working lives at heterogeneous ages. The estimation of the model accounts for this by starting the simulation for each replicated individual at their personal labor force entry age. Entry wages do start at similar levels within the two education groups, independent of the women's age. An overview of the entry ages of the two groups is presented in figure 8. The average entry age for women with low education is around 19.67, while for women with at least some college attendance it is 23.08.

Figure 8: Labor force entry age distribution



Appendix C: External Processes

Appendix C.1 Family Dynamics

All family transition probabilities are estimated using linear probability models, weighted to ensure a similar number of women at each age. When simulating these transitions, predicted probabilities below 0 are reset to 0, and predicted probabilities above 1 are reset to 1. All probabilities are separately estimated for both education groups.

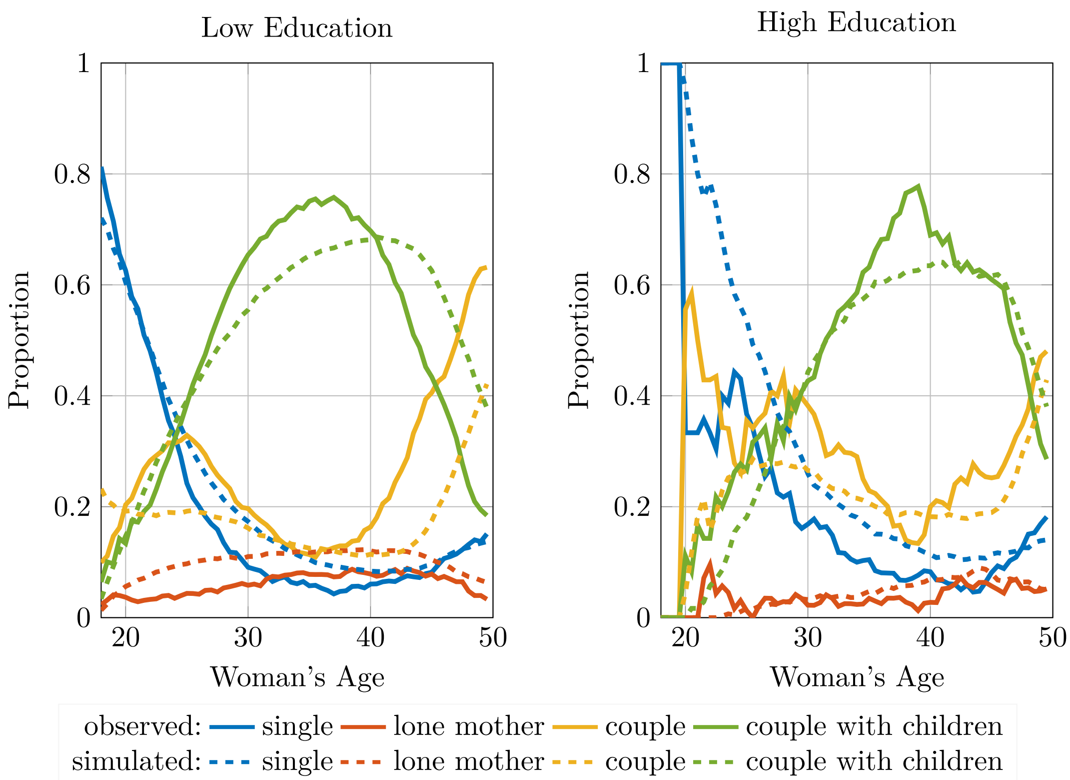
The arrival probability of partners depends on a fifth-order polynomial in the woman's age. The partner departure probability additionally depends on the presence of children. If there are no children present, the probability only depends on a third-order polynomial of the woman's age, while if children are present it depends on a fourth-order polynomial of the women's age and a second-order polynomial of the age of the youngest child.

The probabilities of the arrival of children differ between having a first child and having additional children. All models are separately estimated depending on the presence of a partner. The models for the first child include a fourth-order polynomial in the age of the woman. The models differ substantially with the presence of a partner. If there is partner, an additional birth depends on a third-order polynomial of the mother's age and a third-order polynomial of the age of the youngest child. Furthermore, an interaction term for these ages is added. When there is no partner present, the probability for low educated women only depends on a second order polynomial of the age of the youngest child, and for high educated women only on the first-order polynomial of the age of the youngest child. Using only these few regressors is due to the low number of observations for these groups.[54]

[54] Since the model's decision period is a half-year, women are not able to have an additional child if the youngest child has not yet reached the age of one.

Figure 9 compare the observed family compositions and the simulated family compositions over the life cycle by education. The simulations are reasonably close to the observed family types. Low educated women tend to have their children earlier than higher educated women.

Figure 9: Family Composition by Age and Education



Note: Distribution of family types over the woman's life cycle by woman's education. Low education refers to women not having any college education, while high education to woman having at least some college education. Observed family types are based on SOEP data, while simulated are based on linear probability models estimating partner arrivals, partner departures and the birth of children.

Appendix D: Identification of other parameters

D.0.1 Parameters of the Wage Process

The wage equation depends on the human capital process and its compensation on the labor market. Human capital related to schooling stays constant over the life cycle and builds the base for the wage.[55] The on-the-job human capital accumulates and depreciates depending on the working state

[55] That the schooling does not depreciate can, for example, be interpreted as a signal of the highest degree obtained. The signal does not lose value over the life cycle, although the share of the wage based on schooling decreases when

and is the main driver for wage changes over the life cycle. In principle all parameters are identified by the observed trajectory of the wages depending on the employment state. Since all parameters of the wage process depend on the schooling, but are otherwise identical, I generalize the discussion to a schooling level s'. I start the analysis with the identification of the wage intercepts for schooling in the log wage equation. It can be identified for individuals who have no labor experience as demonstrated below, where the individual index i is dropped for ease of notation:[56]

$$\gamma_{w,s'} = \exp(\mathbb{E}\left[\ln(w_t)|e_t = 0, s = s'\right]) \tag{27}$$

Knowing the schooling's coefficients in the wage equation (3) allows for identifying the coefficient for the compensation of human capital $\gamma_{w,e,s'}$. The easiest way to show its identification is to compare the wage of individuals when they enter the labor market and after they have worked full-time for one period:

$$\begin{aligned} \mathbb{E}[\ln(w_t)|e_t = 0, s = s'] &= \ln(\gamma_{w,s'}) \\ \mathbb{E}[\ln(w_{t+1})|e_t = 0, l_t = FT, s = s'] &= \ln(\gamma_{w,s'}) + \gamma_{w,e,s'} \ln(1.5) \end{aligned} \tag{28}$$

Transforming these equations gives $\gamma_{w,e,s'}$:

$$\gamma_{w,e,s'} = \frac{\mathbb{E}[\ln(w_{t+1})|e_t = 0, l_t = FT, s = s'] - \mathbb{E}[\ln(w_t)|e_t = 0, s = s']}{\ln(1.5)} \tag{29}$$

Given the parameters for the compensation of human capital, the identification of the surplus of a period of part-time work can be archived:

$$\lambda_{s'} = \exp\left(\frac{\mathbb{E}[\ln(w_{t+1})|e_t = 0, l_t = PT, s = s'] - \ln(\gamma_{w,s'})}{\gamma_{w,e,s'}}\right) - 1 \tag{30}$$

For the wage process, only the depreciation rate is left for identification. It can be identified using the subsequent wages of an individual working full-time:

$$\eta_{s'} = 1 - \frac{\exp\left(\frac{\mathbb{E}[\ln(w_{t+1})|e_t = e'_t \neq 0, l_t = FT, s = s'] - \ln(\gamma_{w,s'})}{\gamma_{w,e,s'}}\right) - 1.5}{\exp\left(\frac{\mathbb{E}[\ln(w_t)|e_t = e'_t \neq 0, s = s'] - \ln(\gamma_{w,s'})}{\gamma_{w,e,s'}}\right) - 1} \tag{31}$$

Appendix D.1 Identification of Consumption Preferences

The preference parameters in the model, i.e. the parameters of the utility function, should generally be identifiable, given the distribution for the choice-specific error terms, the discount factor, and the normalization of the utility for one choice (Magnac & Thesmar, 2002). I discuss the identification of the $CRRA$ parameter in the model in more detail. Having identified the parameters of the wage

accumulating on-the-job human capital.

[56] Note that the expectation of $\mathbb{E}[\xi_{i,t}] = 0$.

process and knowing the parameters of the tax and transfer system, the consumption level for all individuals can easily be determined; therefore, I assume c to be given in the following analysis.

Consider the last period in the model and a group of individuals who was working full-time the previous period and with low schooling. The choice probabilities are then given by

$$\Pr(FT|FT,\omega_T) = (1-\pi^L)\frac{\exp(u(FT,\omega_T))}{\sum\limits_{j\in L}\exp(u(j,\omega_T))} \tag{32}$$

$$\Pr(NE|FT,\omega_T) = (1-\pi^L)\frac{\exp(u(NE,\omega_T))}{\sum\limits_{j\in L}\exp(u(j,\omega_T))} + \pi^L \tag{33}$$

Combining the two choice probabilities results in

$$\begin{aligned} \ln\left(\frac{\Pr(FT|FT,\omega_T)}{\Pr(NE|FT,\omega_T)-\pi^L}\right) &= u(FT,\omega_T) - u(NE,\omega_T) \\ &= \frac{c^{1-\gamma_c}-1}{1-\gamma_c}u^L(FT) - \frac{c_u^{1-\gamma_c}-1}{1-\gamma_c} \end{aligned} \tag{34}$$

where c stands for the consumption when working full-time, c_u when being non-employed, and $u^L(FT)$ for the utility derived from leisure when working full-time. Equation (34) has two unknowns, $u^L(FT)$ and γ_c. A necessary condition to identify both parameters is to have at least two independent equations. Additional equations can be generated by having other groups of individuals with slightly higher wages. As long as only relatively low wages are considered, the unemployed benefits can be held constant between these groups.[57] I denote the logarithm of the choice probability ratio by Q_H for a higher consumption level and Q_L for a lower consumption level when employed. Since a higher consumption level when employed increases the probability to choose employment, $Q_H > Q_L$ Solving for $u^L(\gamma_{FT})$, the following can be derived:

$$u^L(\gamma_{FT}) = \frac{1-\gamma_c}{c_L^{1-\gamma_c}-1}Q_L + \frac{c_u^{1-\gamma_c}-1}{c_L^{1-\gamma_C}-1} \tag{35}$$

which can be plugged into equation (34) for the higher consumption level, where $1-\gamma_c$ is summarized by x.

$$Q_H x = x\frac{c_H^x-1}{c_L^x-1}Q_L + \frac{(c_u^x-1)(c_H^x-1)}{(c_L^x-1)} - (c_u^x-1) \tag{36}$$

In addition, if $Q_L, Q_H > 0$,[58] it is possible to derive the following limits of both sides of equation

[57] Another possibility to hold the unemployed benefits constant is to consider individuals with very high incomes, since the unemployed benefits are also capped at a maximum benefit level.

[58] This is the case when $\Pr(FT|FT,\omega_T) > \Pr(NE|FT,\omega_T) - \pi^L$. In the data the probability to be observed in

(36):[59]

$$
\begin{aligned}
\lim_{x\to\infty} & \qquad Q_H x = \infty \\
\lim_{x\to\infty} & \quad x\frac{c_H^x - 1}{c_L^x - 1}Q_L + (c_u^x - 1)\frac{c_H^x - 1}{c_L^x - 1} - (c_u^x - 1) = \infty \\
\lim_{x\to-\infty} & \qquad Q_H x = -\infty \\
\lim_{x\to-\infty} & \quad x\frac{c_H^x - 1}{c_L^x - 1}Q_L + (c_u^x - 1)\frac{c_H^x - 1}{c_L^x - 1} - (c_u^x - 1) = -\infty \\
\lim_{x\to 0} & \qquad Q_H x = 0 \\
\lim_{x\to 0} & \quad x\frac{c_H^x - 1}{c_L^x - 1}Q_L + (c_u^x - 1)\frac{c_H^x - 1}{c_L^x - 1} - (c_u^x - 1) = 0.
\end{aligned} \tag{37}
$$

The left-hand-side and the right-hand-side of equation (36) have an intersection point at zero, but the utility function is not defined for this value. The derivatives close to this point point can be used to find the existence of a solution, in this case a valid intersection point:

$$
\begin{aligned}
\lim_{x\to 0}\frac{\partial LHS}{\partial x} & = Q_H \\
\lim_{x\to 0}\frac{\partial RHS}{\partial x} & = \frac{\ln(c_H)}{\ln(c_L)}Q_L + \ln(c_u)\frac{\ln(c_H)}{\ln(c_L)} - \ln(c_u) \equiv D(Q_L)
\end{aligned} \tag{38}
$$

Whenever $D(Q_L) > Q_H$, that is whenever the slope of the left-hand-side is steeper than the one of the right-hand-side at the origin, the left-hand-side of equation (36) is smaller than the right-hand-side for negative values close to zero. In addition, we have the following derivatives as x approaches $-\infty$:

$$
\begin{aligned}
\lim_{x\to-\infty}\left.\frac{\partial LHS}{\partial x}\right|_{D(Q_L)>Q_H} & = Q_H \\
\lim_{x\to-\infty}\left.\frac{\partial RHS}{\partial x}\right|_{D(Q_L)>Q_H} & = Q_L
\end{aligned} \tag{39}
$$

In the limit, when x approaches $-\infty$, the derivative of the right-hand-side is smaller than the left-hand-side. This is sufficient for the existence of an intersection of both sides. Figure 10 illustrates this case.

The more realistic case is when $D(Q_L) < Q_H$. Then, there is another intersection point in the positive domain of x, since the derivative of the left-hand-side of equation (36) approaches infinity much faster than the right-hand-side as x goes to positive infinity. This is schematically presented in figure 11.

Thus, γ_c is identified as long as $Q_L + \ln\left(\frac{c_H}{c_L}\right) \neq Q_H$. Knowing the parameter of constant relative risk aversion, allows for identifying the leisure preferences for most combinations. Reconsider

employment, when also be employed in the previous period, is over 92% for both education groups.

[59]Note that $\frac{c_H^x - 1}{c_L^x - 1} = \frac{c_H^x - 1}{x}\left(\frac{c_L^x - 1}{x}\right)^{-1}$ and $\lim_{x\to 0}\frac{c^x}{x} = \log(c)$.

Figure 10: Identification of γ_c, when $D(Q_L) > Q_H$

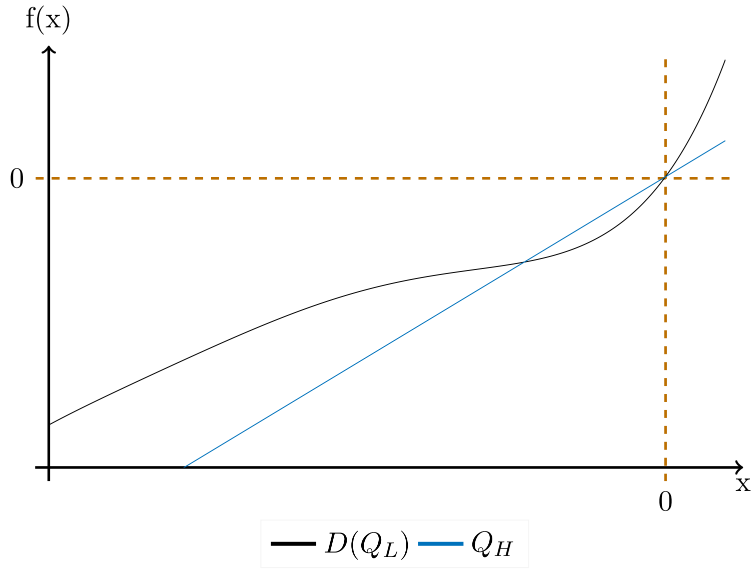
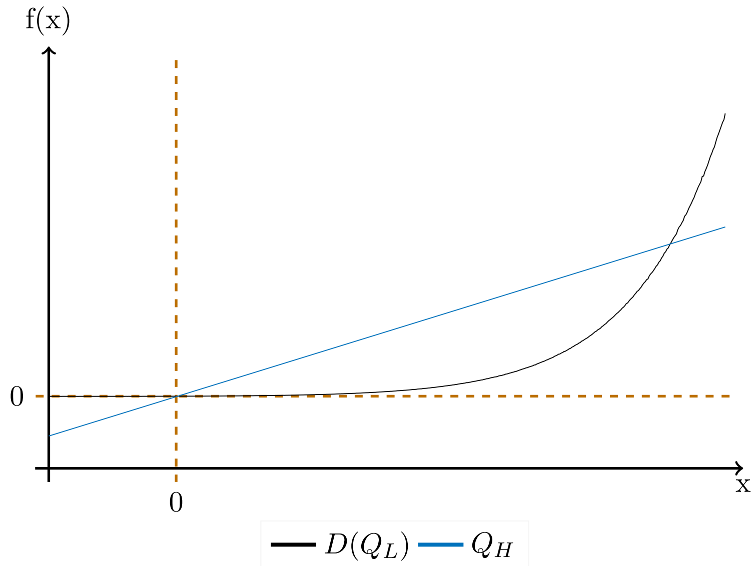


Figure 11: Identification of γ_c, when $D(Q_L) < Q_H$



equation (35), with γ_c and the right-hand-side of this equation is known, and, thus, the leisure utility of working full-time is identified. Similarly, the leisure preferences for part-time and for example in combination of potentially living in a partnership can be identified. One exception are the leisure preferences for children, since there are no young children present in the last period.

D.1.1 Leisure preferences related to the age of the youngest child

Having identified all parameters of the model besides the one related to the utility of leisure depending on the age of the youngest child simplifies their identification. It can be archived by comparing the choice between non-employment and employment of no longer fertile mothers when the youngest child moves out in the next period. The utility of leisure when non-employed is normalized to one and since the woman is no longer fertile, future utilities do not depend on the age of the youngest child.

The following equation can be derived:

$$\begin{aligned}
\ln\left(\frac{\Pr(E|E,\omega_t)}{\Pr(NE|E,\omega_t)}\right) =& \frac{c^{1-\gamma_c}}{1-\gamma_c}u^L(E,a=18) - \frac{c_u^{1-\gamma_c}}{1-\gamma_c} \\
&+ \beta\sum_{\omega_{t+1}}\Big((1-\pi^L)LS(E,\omega_{t+1}) + \pi^L LS(NE,\omega_{t+1})\Big)\, q(\omega_{t+1}|E,\omega_t) \\
&- \beta\sum_{\omega_{t+1}}\Big((1-\pi^L)LS(E,\omega_{t+1}) + \pi^L LS(NE,\omega_{t+1})\Big)\, q(\omega_{t+1}|NE,\omega_t)
\end{aligned} \tag{40}$$

The left-hand-side is directly observable in the data. Since the women are no longer fertile, the future values only depend on already identified parameters. The discount rate β is set in the estimation. Thus, the only part not identified in equation (40) is the utility of leisure depending on an 18 year old child. This utility is, thus, identified. Knowing the value function for a child with age 18, it is possible to go back one half year when the child was 17.5. Similar to the previous argumentation the utility of leisure for a 17.5 year old can be identified. Using this backwards induction, the leisure preferences for all ages of the youngest child can be recovered.

References

Adams, B., Bauman, L., Bohnhoff, W., Dalbey, K., Ebeida, M., Eddy, J., Eldred, M., Hough, P., Hu, K., Jakeman, J., Swiler, L., & Vigil, D. (2013). *DAKOTA, A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 5.4 User's Manual*. Technical report, Sandia Technical Report SAND2010-2183.

Adda, J., Dustmann, C., & Stevens, K. (2017). The Career Costs of Children. *Journal of Political Economy*, 125(2), 293–337.

Altonji, J. G. & Segal, L. M. (1996). Small-Sample Bias in GMM Estimation of Covariance Structures. *Journal of Business and Economic Statistics*, 14(3), 353–366.

Attanasio, O., Low, H., & Sanchez-Marcos, V. (2008). Explaining Changes in Female Labor Supply in a Life-Cycle Model. *American Economic Review*, 98(4), 1517–1552.

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

Bellman, R. (1957). *Dynamic Programming*. Princeton University Press, princeton, edition.

Ben-David, I., Graham, J. R., & Harvey, C. R. (2013). Managerial Miscalibration. *The Quarterly Journal of Economics*, 128(4), 1547–1584.

Bernheim, B. D. (1988). Social Security Benefits: An Empirical Study of Expectations and Realizations. *Issues in Contemporary Retirement*, (pp. 312–345).

Bhargava, B. S. & Manoli, D. (2015). Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment. *American Economic Review*, 105(11), 3489–3529.

Blau, F. D. & Ferber, M. A. (1991). Career Plans and Expectations of Young Women and Men: The Earnings Gap and Labor Force Participation. *Journal of Human Resources*, 26(4), 581–607.

Blundell, R., Costas-Dias, M., Meghir, C., & Shaw, J. M. (2016). Female Labour Supply, Human Capital and Welfare Reform. *Econometrica*, 84(5), 1705–1753.

Chan, M. K. (2017). Welfare Dependence and Self-Control: An Empirical Analysis. *Review of Economic Studies*, 84(4), 1379–1423.

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

Davidson, R. & MacKinnon, J. G. (2000). Bootstrap tests: how many bootstraps? *Econometric Reviews*, 19(1), 55–68.

De Bondt, W. F. M. & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. In R. Jarrow, V. Maksimovic, & W. T. Ziemba (Eds.), *Handbooks in Operations Research and Management Science*, Volume 9, Chapter 13, (pp. 385–410). Amsterdam: North Holland.

DellaVigna, S., Lindner, A., Reizer, B., & Schmieder, J. F. (2017). Reference-Dependent Job Search: Evidence from Hungary. *The Quarterly Journal of Economics*, 132(4), 1969–2018.

DellaVigna, S. & Paserman, M. D. (2005). Job Search and Impatience. *Journal of Labor Economics*, 23(3), 527–588.

Dolls, M., Doerrenberg, P., Peichl, A., & Stichnoth, H. (2016). Do savings increase in response to salient information about retirement and expected pensions? *NBER Working Paper 22684*.

Duflo, E. & Saez, E. (2003). The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment. *The Quarterly Journal of Economics*, 118(3), 815–842.

Eckstein, Z. & Wolpin, K. I. (1989). Dynamic Labour Force Participation of Married Women and Endogenous Work Experience. *The Review of Economic Studies*, 56(3), 375–390.

Federal Reserve Bank of St. Louis (2016). Organization for Economic Co-operation and Development, Consumer Price Index of All Items in Germany [DEUCPIALLMINMEI].

Federal Reserve Bank of St. Louis (2017a). OECD based Recession Indicators for Germany from the Period following the Peak through the Trough [DEUREC].

Federal Reserve Bank of St. Louis (2017b). Organization for Economic Co-operation and Development, Registered Unemployment Rate for Germany [LMUNRRTTDEM156S].

Gourieroux, C., Monfort, A., & Renault, E. M. (1993). Indirect inference. *Journal of Applied Econometrics*, 8, S85—-S118.

Gronau, R. (1988). Sex-Related Wage Differentials and Women's Interrupted Labor Careers - the Chicken or the Egg. *Journal of Labor Economics*, 6(3), 277–301.

Haan, P., Haywood, L., & Schneider, U. (2017). Time Preferences and Female Labor Supply. *Mimeo*.

Haan, P. & Prowse, V. (2017). Optimal Social Assistance and Unemployment Insurance in a Life-cycle Model of Family Labor Supply and Savings. *IZA Discussion Paper No. 8980*.

Hamermesh, D. S. (1985). Expectations, Life Expectancy, and Economic Behavior. *The Quarterly Journal of Economics*, 100(2), 389–408.

Heckman, J. J. & Macurdy, T. E. (1980). A Life Cycle Model of Female Labour Supply. *The Review of Economic Studies*, 47(1), 47–74.

Hoffman, M. & Burks, S. V. (2017). Worker Overconfidence: Field Evidence and Implications for Employee Turnover and Returns from Training. *NBER Working Paper 23240*.

Hotz, V. J. & Miller, R. A. (1993). Conditional Choice Probabilities and the Estimation of Dynamic Models. *The Review of Economic Studies*, 60(3), 497–529.

Hurd, M. D., Smith, J. P., & Zissimopoulos, J. M. (2004). The effects of subjective survival on retirement and social security claiming. *Journal of Applied Econometrics*, 19(6), 761–775.

Kassenboehmer, S. C. & Schatz, S. G. (2017). Re-employment expectations and realisations: Prediction errors and behavioural responses. *Labour Economics*, 44(October 2016), 161–176.

Keane, M. P., Todd, P. E., & Wolpin, K. I. (2011). The Structural Estimation of Behavioral Models: Discrete Choice Dynamic Programming Methods and Applications. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics*, Volume 4a, Chapter 4, (pp. 331–461). Elsevier.

Kleven, H. J. & Waseem, M. (2013). Using Notches To Uncover Optimization Frictions and Structural Elasticities: Theorie and Evidence from Pakistan. *The Quarterly Journal of Economics*, 128(2), 669–723.

Kruger, J. & Dunning, D. (1999). Unskilled and unaware of it: How Difficulties in Recognizing One's Own Incompetence Lead to Inflated Self-Assessments. *Journal of Personality and Social Psychology*, 77(6), 1121–1134.

Low, H., Meghir, C., & Pistaferri, L. (2010). Wage Risk and Employment Over the Life Cycle. *American Economi Review*, 100, 1432–1467.

Magnac, T. & Thesmar, D. (2002). Identifying Dynamic Discrete Decision Processes. *Econometrica*, 70(2), 801–816.

Malmendier, U. & Taylor, T. (2015). On the Verges of Overconfidence. *Journal of Economic Perspectives*, 29(4), 3–8.

Manski, C. F. (1990). The Use of Intentions Data to Predict Behavior: A Best-Case Analysis. *Journal of the American Statistical Association*, 85(412), 934–940.

Manski, C. F. (2004). Measuring Expectations. *Econometrica*, 72(5), 1329–1376.

Moore, D. A. & Healy, P. J. (2008). The Trouble with Overconfidence. *Psychological Review*, 115(2), 502–517.

Rees-Jones, A. (2017). Quantifying Loss-Averse Tax Manipulation. *The Review of Economic Studies (forthcoming)*.

Saez, E. (2010). Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy*, 2(3), 180–212.

Sandell, S. H. & Shapiro, D. (1980). Work Expectations, Human Capital Accumulation, and the Wages of Young Women. *Journal of Human Resources*, 15(3), 335–353.

Schoenberg, U. & Ludsteck, J. (2014). Expansions in Maternity Leave Coverage and Mothers' Labor Market Outcomes after Childbirth. *Journal of Labor Economics*, 32(3), 469–505.

Shaw, L. B. & Shapiro, D. (1987). Women's work plans: contrasting expectations and actual work experience. *Monthly Labor Review*, 110, 7–13.

Sheran, M. (2007). The career and family choices of women: A dynamic analysis of labor force participation, schooling, marriage, and fertility decisions. *Review of Economic Dynamics*, 10(3), 367–399.

Slovic, P. (2000). *The Perception of Risk*. Earthscan.

Spinnewijn, J. (2015). Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs. *Journal of the European Economic Association*, 13(1), 130–167.

Svenson, O. (1981). Are We All Less Risky and More Skillful than Our Fellow Drivers? *Acta Psychologica*, 47, 143–148.

Tversky, A. & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, 5, 207–232.

Tversky, A. & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), 1124–31.

Van der Klaauw, W. (1996). Female Marital Labour Status Supply Model and Decisions: A Life-Cycle Model. *The Review of Economic Studies*, 63(2), 199–235.

Vaskovics, L. A. & Rost, H. (1999). Väter und Erziehungsurlaub. In *Schriftenreihe des Bundesministeriums für Familie, Senioren, Frauen und Jugend*, Number 179. Stuttgart: Kohlhammer.

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

Weinstein, N. D. (1980). Unrealistic Optimism About Future Life Events. *Journal of Personality and Social Psychology*, 39(5), 806–820.

Wrohlich, K. (2011). Labor Supply and Child Care Choices in a Rationed Child Care Market. *DIW Berlin Discussion Paper No. 1169.*

Zmarzlik, J., Zipperer, M., & Viethen, H. P. (1999). *Mutterschutzgesetz, Mutterschaftsleistungen, Bundeserziehungsgeldgesetz - mit Mutterschutzverordnung.* Köln: Heymanns, 8th edition.