Essays in Applied Econometrics

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Chapter 1

Introduction

This dissertation analyzes three independent topics based on two different kinds of datasets, the German Socio Economic Panel (SOEP) and the Austrian Social Security Database (ASSD). Chapter 2 analyzes differences in expectations and realizations in return migration using the SOEP. Chapter 3 analyzes bereavement and early life outcomes also using this dataset. While Chapters 4 and 5 analyze employment based networks and displacement in the context of the labor market using the ASSD. The SOEP is a representative longitudinal survey of households and their members in Germany conducted for over 25 years. The SOEP's aim is to collect representative micro-data on individuals, households and families in order to measure stability and change in living conditions. The ASSD is a matched employer-employee database, which covers the universe of private sector workers covered by the social security system in Austria between 1972 and 2009. It provides daily information on employment, registered unemployment, total annual earnings paid by each employer, and various individual characteristics of the workers as well as information on employers such as geographical location, industry, and size.

Duration analysis is used, to analyze personal preferences in Chapter 2 and to analyze job search outcomes, such as unemployment duration for individuals displaced through firm closures, and network characteristics in Chapter 4. Chapters 3 and 5 on the other hand use first differences to get rid of individual unobservables, in order to explore bereavement effects in combination with early life circumstances experienced during the Second World War (WW2) in Chapter 3. While Chapter 5 analyzes whether "lemons" or self-selection are observed in the labor market. A brief overview of the separate chapters follows.

Explaining Differences Between the Expected and Actual Duration Until Return Migration: Economic Changes and Behavioral Factors In Chapter 2 which is co-authored with Gerard J. van den Berg, we are able to analyze individual preferences exploiting the panel structure of the dataset. The main questions in this chapter are whether there is a difference between the expected duration of stay (which is given by the individual) and the actual duration (which we observe if they return) and if so, can it be explained. Using a duration model to get the realized return for the non-returners, we find evidence that migrated individuals use simplifying heuristics when trying to forecast the future. Their return intentions indicate bunching in heaps of 5 years (e.g., intend to return in 5, 10, 15 years). Along these lines we find that migrated individuals systematically underestimate the length of their stay in the receiving country. The average forecast error is therefore mostly negative but decreases the longer the person stayed in Germany and the older she gets. Furthermore we use behavioral factors to explain the difference between the intentions and the realized return. We find that being older than 60 years, reduces the difference considerably, while if an individual feels disadvantaged due to her origin, her forecast error increases. An individual, who is remitting over the course of her stay, is also underestimating the duration of her stay, while someone with a high locus of control is better at predicting the duration of her stay. The robustness checks show that the results do not hinge on a single definition or a set of explaining variables. The consistency in the underestimation may have important policy and modeling implications for future research, as it may hinder proper integration.

Bereavement Effects and Early Life Circumstances This chapter is co-authored with Gerard J. van den Berg and Anna Hammerschmid, and is based on the SOEP combined with a novel dataset on early childhood in the (post) war context (FKM - "Frühe Kindheitsmodul"). We use a first difference approach to explore bereavement effects and early life circumstances such as exposure to combat actions, air raids and father's absence in and after the Second World War (WW2) on mental resilience, life satisfaction and satisfaction sleep. We find more detrimental bereavement effects for individuals who have experienced these early life circumstances. Our results underline the importance of the early life environment to develop the ability to cope with grief later in life. This "indirect" effect of adverse conditions in utero or childhood once more emphasizes the importance of policy interventions protecting children and helping them to deal with traumatic events. Moreover, such policies could reduce health care costs and productivity loss related to bereavement later in life.

Coworkers, Networks and Job Search Outcomes This chapter is co-authored with Perihan Saygin and Andrea Weber and uses the ASSD to evaluate how displaced workers benefit from their social networks. Social networks are an important channel of information transmission in the labor market. In this chapter we study the mechanisms by which social networks impact the labor market outcomes of displaced workers. Our primary objective is to explore whether social contacts relate general information about job opportunities and search strategies or if they provide specific information in terms of job referrals to vacancies at their own workplace. We base our analysis on administrative records for the universe of private sector employment in Austria and identify displaced workers who lose their jobs from firm closures. The network definition focuses on work-related networks formed by past coworkers. To distinguish between the mechanisms of information transmission, we adopt two different network perspectives. From the job-seeker's perspective we analyze how network characteristics affect job finding rates and wages in the new jobs. Then we switch to the hiring firms' perspective and analyze which types of displaced workers get hired by firms that are connected to a closing firm via past coworker links. Our results indicate that employment status and the firm types of former coworkers are crucial for the job finding success of their displaced contacts. Moreover, 25% of displaced workers find a new job in a firm that is connected to their former workplace. Among all workers that were displaced from the same closing firm those with a direct link to a former coworker are three times more likely to be hired by the connected firm than workers without a link. These results highlight the role of work related networks in the transmission of job related information and strongly suggest that job referrals are an important mechanism.

Selective Firing and Lemons? This chapter uses the ASSD to explore what information firms infer from the three common types of displacement: individual layoffs, individuals displaced due to a closure and individuals displaced due to a mass layoff. This chapter thereby brings together two strands of the literature, namely signaling and sorting. The contribution to the literature is threefold. First I test whether the individual layoffs are the least productive, second I investigate whether individual layoffs are perceived as "lemons" (with a specific focus on the high ability individuals) and third I raise the question whether the "lemon" exists in the resulting matching pattern. Using the Abowd et al. (1999) model, I show that the individual layoffs are the least productive measured by the person fixed effect. I confirm the signaling argument of Gibbons and Katz (1991) that individual layoffs are perceived as "lemons" also for high ability individuals, but reject the argument of Gibbons and Katz (1991) against the matching model (Becker, 1973). Using three different measures of sorting, I find that the matching changes differentially for the different layoff groups. This leads to the tentative conclusion that both sorting and signaling take place after an individual job loss.

Relationship to previous own work. This thesis consists of five chapters, and includes four distinct research papers. All chapters were exclusively created during my time at the University of Mannheim or at the University of California, Berkeley. Chapter 2 extends my own work Weynandt (2011) and van den Berg and Weynandt (2013). Weynandt (2011) was a preliminary version of Chapter 2 and was handed in at the University of Mannheim as my Master Thesis. Weynandt (2011) deals with the model selection, and includes similar or identical parts compared to Chapter 2 in the literature section, the data section and the empirical specification. There are however several key contributions that are new to this thesis. Compared to Weynandt (2011) the main differences lie in the empirical specification and the result section, since we added the difference between the intentions and the expectations and did not just discuss the model fit of the duration model. Compared to van den Berg and Weynandt (2013), where we analyze whether economic changes can explain the difference between the expected and actual return, this thesis adds behavioral factors, such as life satisfaction and narrow framing. Two important extensions as these behavioral factors may be one explanation for the discrepancy between the expected return and the actual return in migration.

Chapter 2

Explaining Differences Between the Expected and Actual Duration Until Return Migration: Economic Changes and Behavioral Factors[1]

2.1 Introduction

This chapter explores the fact that migrated individuals underestimate the length of their stay in the receiving country. "Hedonic forecasting" refers to the errors that individuals make in predicting changes in their tastes and feelings in the psychological literature. The reader is presented with evidence of a forecasting error and convincing statistics proving that it is not just simple noise. Loewenstein et al. (2003) have defined the suggestion that people understand the qualitative nature of changes in their tastes, but underestimate the magnitude of these changes, as projection bias.

Looking at return migration and the expectation to return, our prior is that people underestimate their attachment to the country of migration - when first moving away from home, one compares everything to home. Most of the time, the culture in the country of migration will be different, one will not know a lot of people and one may not even have family in the migrating country. All these things are examples of what a person might miss when first moving to a new country.

[1]This chapter is co-authored with Gerard J. van den Berg. A shorter version of this chapter is published as van den Berg and Weynandt (2013) where we analyze the economic changes only. A preliminary version of the first part of the chapter, dealing with the model selection was handed in at the University of Mannheim as my Master Thesis, Weynandt (2011).

Furthermore as discussed in Card et al. (2012a), prejudices from natives against migrants may hamper the adaptation and the process of feeling at home in Germany. Therefore when people are asked whether they want to return, most of them say yes because they miss the culture, the food and so on.[2]

Once the individual has fully arrived in the migrating country - Germany for the current analysis - one starts to meet new people, gets to know people on the job (assuming that you have a job) and starts to discover things about Germany that may not have been known in advance. This process of integrating and feeling at home in Germany is what we call net attachment in the following. Upon arrival to Germany, the net attachment is very low, even though one decided to migrate. The decision why people migrated in the first place underlies the current analysis and the focus lies on those migrants that are already in Germany.

The German Socio-Economic Panel (SOEP) is used for the analysis as individuals provide information on their return intentions. Using a duration model we infer an expression for the predicted return realization - an expected duration of the stay in the receiving country. This predicted return will then be compared to the respondents intentions and will then be regressed on different sets of socio-economic variables, which allows for the identification of the driving factors between return intentions and return realizations.[3]

A first important finding, is that people's intentions exert bunching which already points towards the fact that a simplifying heuristic may be at work. Taking a closer look at the difference between the intentions and the realizations, we see that the intentions lie constantly below the realization. Individuals considerably underestimate the duration of their stay. The average forecast error is therefore mostly negative but decreases with the length of the stay in Germany and the age.[4] Using pooled OLS, we are able to identify a few other factors that drive the difference between intentions and realizations. Being older than 60 years, reduces the difference considerably, while if an individual feels disadvantaged due to her origin, her forecast error increases. An individual, who is remitting over the course of her stay, is also underestimating the duration of her stay,

[2]Individuals that came to Germany due to a war or as refugees on the other hand may not want to return to their country ever. These individuals are of no worry for the current analysis, since they should predict that they want to stay in Germany forever.

[3]Please be aware that we are not claiming a causality of the results. We are only interested in the driving factors of the forecast error.

[4]The difference between the intentions and the predicted return and forecasting error will be used interchangeably in the following since they refer to the same measure.

while someone who has a high locus of control is better at predicting the duration of their stay.

A very good understanding of the difference between expectations and realizations in return migration is crucial for integration policies. If migrants consistently underestimate the duration of their stay, they may not put enough effort into their integration. Government interventions may help to improve the situation for migrants by emphasizing on integration as early as possible. It is important to understand these differences to avoid conflicts of integration between current inhabitants and migrants.

The setup of the chapter is as follows; Section 2.2 gives an overview of the relevant literature in return migration, 'hedonic' forecasting and projection bias. Section 2.3 presents the data and some preliminary results, while Section 2.4 presents the model and the empirical specification. Section 2.5 presents the results and Section 2.6 concludes.

2.2 Literature

The literature overview is split into two subsections, where first return migration is discussed, and second "hedonic forecasting" and projection bias are explained with their relevant literature.

2.2.1 Return Migration

This subsection reviews a few groundbreaking papers in the field of return migration, which provide the underlying economic framework of the decision process; whether an individual should return or not. A first paper working out the details of return migration is the work of Borjas and Bratsberg (1996) who generalize the model of Borjas (1991) by allowing migrants to return. Borjas and Bratsberg (1996) mention two possible alternatives for return migration; one possibility is that return migration is part of the life-cycle and a second possibility is that the initial decision is based on erroneous information about economic opportunities in the receiving country, which then forces migrants to revise their information and return. Borjas and Bratsberg (1996) work focuses on the first possibility; the life-cycle argument.

Dustmann (2003b) complements Borjas and Bratsberg (1996) by adding two reasons for re-migration; either the returner has a relatively high preference for consumption at home or there is a higher purchasing power of the host country's currency in the sending country.
Likewise Dustmann (2003a) examines return motives of migrant parents and finds that parents who have a daughter are more likely to return to their home country than those that have a son.

He explains his finding through the importance in cultural differences when raising a child. In other words, Dustmann (2003a) uses an altruistic model to show that “parental concerns about the child may lead to an increase or to a decrease in the tendency to return to the home country”.

Dustmann and Weiss (2007) ream the above cases that return migration may occur because of a preference for home country consumption, a decision which would increase the migrants lifetime wealth. Along the lines of Borjas and Bratsberg (1996) life-cycle argument, Dustmann and Weiss (2007) claim that the benefits of migration decrease over the migration cycle, while costs are positive and may even increase. Dustmann et al. (1996) expand Borjas and Bratsberg (1996) life-cycle criteria by asserting that migrants may acquire skills in the receiving country that could be more valuable in their home country. As such the receiving country would be an education stop in their life-cycle. This reasoning goes along the lines of selective outmigration, where an example would be Van Hook and Zhang (2011) who find that emigration is positively associated with factors such as having a spouse in another country.

Another strand in the literature discusses the duration of stay and migratory frequency, usually illustrated by migration between Mexico and the United States (Hill (1987), Lindstrom (1996), Reyes (2001), Reyes (2004), Hill and Wong (2005), Durand et al. (1996)). Mexican migrants are frequent migrants, since they cross the border several times for a short period of time. They make about 4 or 5 trips and on average stay 6 months to a year per trip (Cornelius (1978), Jenkins (1977)).

The distinguishing feature of the current work is that it focuses on the underestimation of the trip duration. The aforementioned literature discussed reasons for return migration, and as such constitutes the underlying component for the current work. Section 2.2.2 presents the concepts of “hedonic” forecasting and projection bias.

2.2.2 Hedonic Forecasting and Projection Bias

A first and often cited example, in the hedonic forecasting and projection bias literature, is the work of Read and van Leeuwen (1998) regarding the prediction of hunger. They asked a group of hungry and a group of satiated people what kind of snack - healthy or unhealthy - they wanted in a week at a time where both groups would be satiated (in the afternoon). Read and van Leeuwen (1998) found that the satiated group opted for the healthy snack while the hungry group prefered the unhealthy snack. Another paper on the same topic, Gilbert et al.

(2002) looked at people who were hungry and suggested that they acted as if their future taste for food would reflect such hunger. Nisbett and Kanouse (1968) suggested that shopping on an empty stomach may lead people to buy too much. Not just studies of hunger showed evidence of projection bias; Badger et al. (2007) studied 13 long time adult heroin addicts who had been regularly receiving BUP and noticed that their expectations differed from the realized craving.[5] Based on this evidence, Loewenstein et al. (2003) formalized projection bias in predicting future utility.

It is well known that people adapt to changes, but the above cited literature presented evidence that people underestimate adaptation. Conlin et al. (2007) clearly demonstrated how people exert projection bias by analyzing catalog orders. They were able to show that people were more likely to return winter clothes when the temperature on the receiving date climbed compared to the order date temperature. Gilbert et al. (1998) reported several instances of people underestimating adaptation to unfavorable events (which they labeled immune neglect). A recent paper by Levy (2009) was able to pin down the projection bias in tobacco consumption. Furthermore Acland and Levy (2010) suggested that gym goers in an incentivized gym-use experiment do not appreciate the positive addiction of exercise regimes.

Stephens (2004) on the other hand examined the relationship between job loss expectations and realizations, and as such his focus is closer to the one considered in the current work. His work has two important outcomes; first he found that people's expectation were a good predictor of actual job loss. He found a positive correlation between the intention and the actual state, as such the expectation contained information that the econometrician could not infer from the demographics or other covariates. Second he discovered that workers in the HRS tended to overstate their job loss probability which is another important finding as one can see the connection to the underestimation of net attachment.

This chapter contributes to the above mentioned literature by showing that people exert not just a prediction bias in food related issues, clothing or employment, but also in migration decisions. In addition, the goal of this work is to analyze people's ability to adapt their expectations over time and possibly show that their expectations converge to the truth in the long run. Levy (2009) and Acland and Levy (2010) look at habit formation over time and are able to show that

[5]BUP stands for buprenorphine which is a drug that acts by relieving the symptoms of opiate withdrawal. http://www.employee-drug-testing-ace.com/employment-drug-screening-resources/employee-drug-testing-glossary/define-buprenorphine-bup.

people underestimate their addiction.

2.3 Data and Presence of a Bias

Subsection 2.3.1 presents the Data, while Subsection 2.3.2 provides evidence of projection bias in people's expectations.

2.3.1 Data

This chapter uses the German Socio-Economic Panel (henceforth SOEP) to analyze the difference between return expectations and return realizations of migrants to Germany.[6] The SOEP is a representative longitudinal survey of households and their members, whose aim is to collect representative micro-data on individuals, households and families in order to measure stability and change in living conditions. The SOEP annually re-interviews households and their split-offs, usually in February and March. We use data from 1984 until 2010 for the analysis which enables the duration analysis approach. The sample of the first wave (1984) includes about 1500 households with a foreign born head. Furthermore the SOEP surveys the respondents intention, an important point in order to analyze the bias, by asking migrants about their desire to remain in Germany. First the respondent is asked whether she wants to return home, which can be answered by yes or no (stay in Germany forever). If she plans to return, there are two possible answers: "return within 12 months" or "return in a few years". If the plan is to return "in a few years" an intended amount of years that she plans to remain in Germany has to be provided to the interviewer.

The information about whether or not people return to their country of origin is provided by the SOEP in the so called "address log" - where reasons for non-response are logged. The "address log" is recorded at the household level and has as possible options; "moved obtained address", "address of the household not found", "address unknown", "moved out of Germany" or "died". "Moved out of Germany" is used to code the migrant's return.

Using the return status we are able to infer the expected return (for the non-returners) through duration analysis, the predicted expectations will be compared to the given intentions.[7] GDP is

[6]To get a more thorough overview of the data, we refer you to Wagner et al. (2007) and Haisken-DeNew and Frick (2005).

[7]We refer the reader to the Section 2.4 for further details on the duration model for the expected return.

used as a proxy for the life conditions in the home country and as a proxy of the possible wage in the sending country which is necessary to infer the predicted return. The GDP levels for the different countries are from Angus Maddison but are only available until 2008, which forces the drop of the year 2009 and leaves 25 years for the analysis (1984-2008).[8] The Maddison data was chosen because it incorporates most countries of origin for the migrants in the current sample. Furthermore the GDP levels are in 1990 International Geary-Khamis (GK)$.

2.3.2 Presence of a Bias

To illustrate the actual returns Table 2.1 presents the number of returns across the years. People that have not returned until 2009 are coded as non returners for Table 2.1 and all upcoming results. From a duration analysis point of view these observations are right censored. As can be seen in Table 2.1 overall close to 23% return over the course of 25 years, from 1985 until 2009, while on the annual level about 1% of individuals return.[9]

Table 2.1: Return Frequency

Year	85	86	87	88	89	90	91	92	93	94	95	96	97
Ret.	117	33	37	53	33	28	17	23	24	29	27	41	23
Pct	3.70	1.04	1.17	1.68	1.04	0.89	0.54	0.73	0.76	0.92	0.85	1.30	0.73

Year	98	99	00	01	02	03	04	05	06	07	08	09	Tot.
Ret.	39	27	24	23	15	11	23	14	16	13	17	14	721
Pct	1.23	0.85	0.76	0.73	0.47	0.35	0.73	0.44	0.51	0.41	0.54	0.44	22.8

Source: SOEP, own calculations.
Note: Ret. stands for Return, while Pct stands for Percent and Tot stands for Total.

A comparison between the actual and the intended return provides evidence that people's expectations differ from their actions. Evidence that people may exhibit projection bias in forecasting their future is presented in Table 2.2.[10] About 70% of those expressing the intention to return to their home country, over the course of 25 years never do.[11] As mentioned above when evaluating Table 2.2 keep in mind that some people may have been wrongly coded as non returners. They can still return but it cannot be observed due to right censoring. A further thing

[8] http://www.ggdc.net/MADDISON/Historical Statistics/horizontal-file 02-2010.xls.

[9] Table 2.1 should look similar to Table 1 in Dustmann (2003a), as you can see by comparing our table with his (reproduced in the appendix Table 2.13), our numbers are smaller than his. In the appendix we discuss possible explanations for these differences.

[10] In the appendix (Table 2.14) the comparison between the intended and the actual return from 1984-1997 is provided in order to make it possible to compare these results to Dustmann (2003a), but again the numbers differ.

[11] As can be seen by comparing Table 2.2 with Table 2.15 the overall numbers do not change much when the time horizon is enlarged by 12 years, from 1984-1997 to 1984-2009.

to note, is that it is impossible to capture short term migration lasting no longer than one year. The SOEP surveys people annually, thereby not allowing the account of people that migrate and return within a year.[12]

Table 2.2: Intentions and Realization 1984 - 2009

	Return between 84 and 09		
Intended Return (84)	No	Yes	Total
No	682	82	764
Column Percentage	30.00	16.05	27.44
Row Percentage	89.27	10.73	
Yes	1591	429	2020
Column Percentage	**70.00**	83.95	72.56
Row Percentage	78.76	21.24	
Total	2273	511	2784

Notes: This table only presents statistics for people present in 1984.
Source: SOEP, own calculations.

A valid concern in assessing the above numbers is that individuals do not report the truth to the interviewer when asked about their desire to return. Some people may lie about their planned duration in Germany because their current visa only allows them to stay for a limited amount of time. Since the SOEP provides information on a migrant's residence status, which is either unlimited or limited, Table 2.3 presents the comparison between the desire to return and the residence permit question. About 70% of those that have a limited residence permit in Germany reply that they want to remain forever in Germany. As a consequence one cannot argue that people tend to lie due to their residence permit. As it may be easy to get the residential permit prolonged people respond truthfully when asked about their intentions.[13]

As we have seen up to this point, there is evidence of a bias between people's expectation and their final actions in the case of return migration. Table 2.4 takes a closer look at the socio-economic differences between movers and stayers.

[12]These individuals do not play an important role for the analysis of the underestimation of the trip duration.

[13]Note that in Table 2.3 there are three different possible answers for the desire to return home, while in Table 2.2 the intention to return home was coded as a yes or no. If people answered that they want to stay in Germany, their intentions to stay was coded as a yes, while if people answered that they either plan to return within 12 months or after 1 year, their intentions to stay were coded as a no. Be aware that in Table 2.3 the information that is available across all years from 1984 until 2009 is used, while Table 2.2 only considers those people that are present in 1984. Unfortunately it is not possible to present a table with those individuals present in 1984, since for everyone of them the residence status is missing - an unfortunate side effect of survey data. Tables 2.16 and 2.17 in the appendix include the same baseline year, a group of people for whom the residence permit status is known and for whom the intentions are known. 1996 is the first year this happens which shortens the time horizon notably.

Table 2.3: Desire to Return versus Residence Status

	Residence Status		
Desire to Return	Unlimited	Limited	Total
Within 12 Months	22	24	46
(Percentage)	0.79	1.48	1.04
After One Year	766	444	1210
Percentage	27.47	27.44	27.46
Stay in Germany Forever	2000	1150	3150
Percentage	71.74	**71.08**	71.49
Total	2788	1618	4406

Source: SOEP, own calculations.

Table 2.4: Socioeconomic Differences

	Stayers			**Leavers**			
Variable	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**t-stat**
Male	0.50	0.50	3891	0.44	0.50	574	(-2.56)*
Age at Migration	30.04	10.66	3891	30.79	9.34	574	(1.59)
$\ln(GDP_G)$-$\ln(GDP_H)$	1.69	1.10	3838	1.69	1.06	568	(0.05)
Married	0.65	0.48	3564	0.38	0.49	471	(-11.50)***
Married living separated	0.02	0.15	3564	0.02	0.14	471	(-0.43)
Divorced	0.05	0.22	3564	0.01	0.12	471	(-3.54)***
Widowed	0.05	0.22	3564	0.03	0.16	471	(-2.56)*
Employed	0.52	0.50	3890	0.44	0.50	574	(-3.65)***
Family at Home	0.19	0.39	3876	0.07	0.25	569	(-7.32)***
Spouse at Home	0.02	0.13	3891	0.08	0.27	574	(9.25)***
Attended School in Germany	0.03	0.17	3832	0.02	0.16	566	(-0.85)

Source: SOEP, own calculations.
Note: The t-statistics test for the significance of the difference between leavers and stayers. For each individual the last point in time where information is provided in the dataset is taken to get the different means.

There seem to be socio-economic differences between movers and stayers, a finding which goes along with the findings of e.g., Van Hook and Zhang (2011). Leavers and stayers seem to differ in certain socio-economic characteristics, e.g., marital status, and employment, which points toward the selection of return migrants.[14]

Figure 2.1: Descriptive Statistics 1

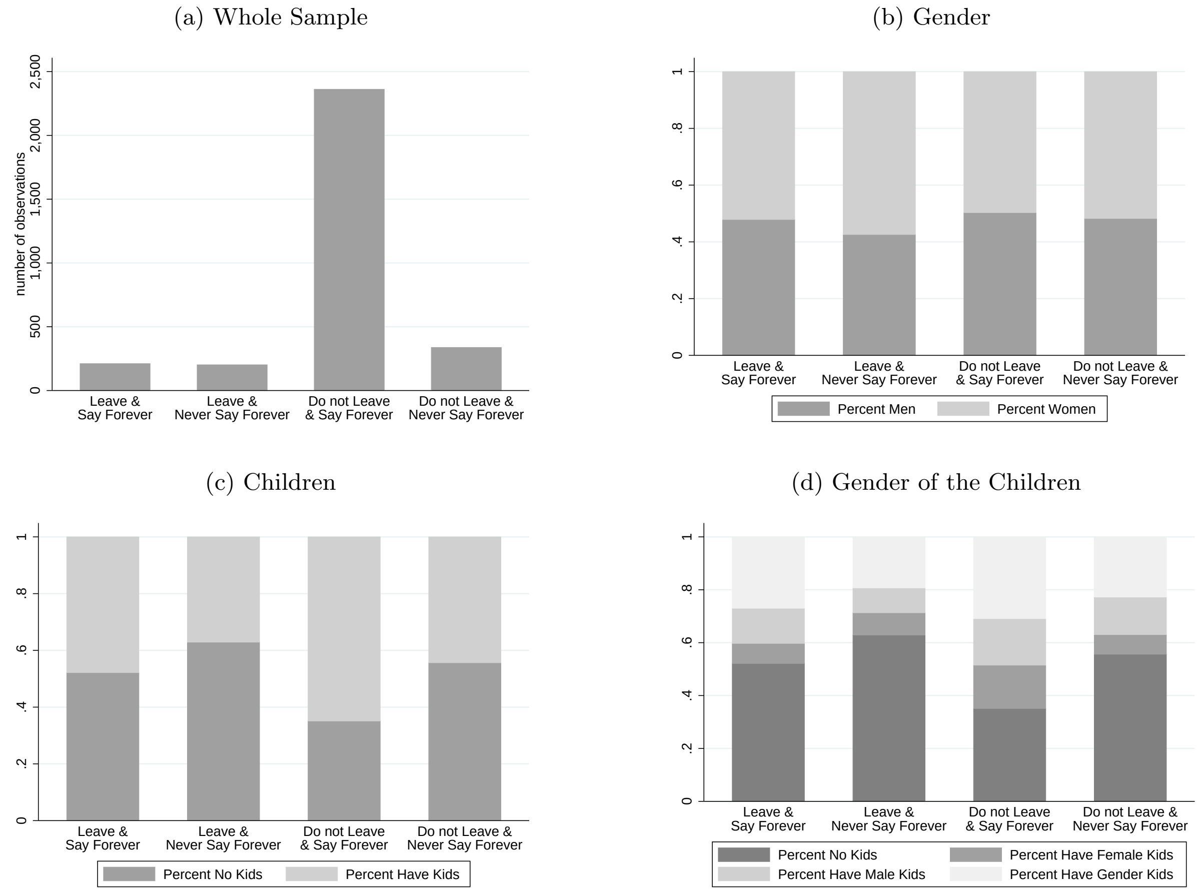
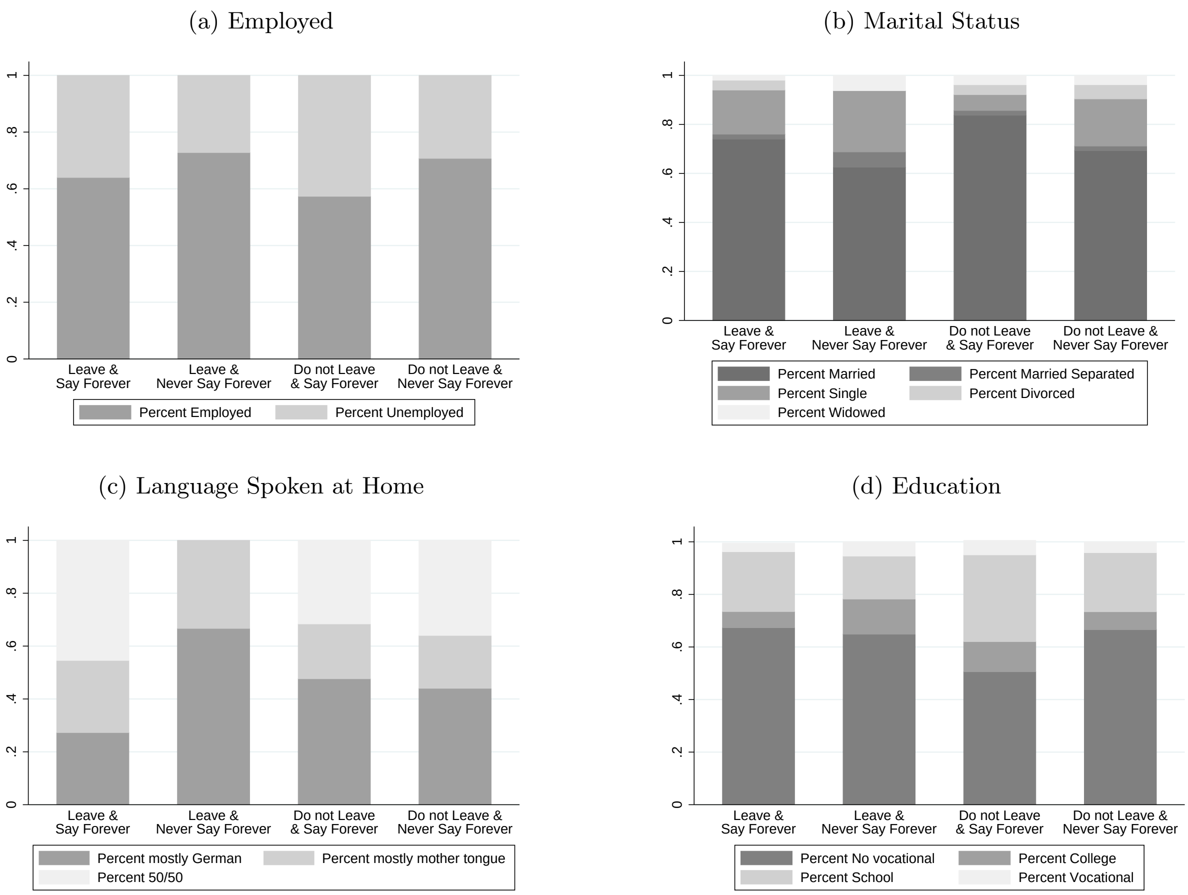


Figure 2.1 and 2.2 contrast the descriptive statistics of the four possible groups. In our sample we have leavers who never say that they want to remain forever, leavers who at some point say that they want to remain forever and non leavers who either say hat they want to remain forever or never say that they want to stay forever. Figure 2.0a shows the number of observations for the different groups. The group that at some point said that they wanted to remain forever and have not yet left constitute the largest group. Figure 2.0b takes a closer look at the gender composition of the different groups. There seem to be no significant differences in gender between the different groups. Figure 2.0c looks at whether children are present. Here we see that those

[14]Table 2.18 in the appendix splits the "stayers" into attritors and those individuals that we observe until 2008 and have not returned yet.

Figure 2.2: Descriptive Statistics 2

(a) Employed (b) Marital Status (c) Language Spoken at Home (d) Education



individuals that have children are more likely to be in the group that says at some point that they want to remain forever and have not left so far. Figure 2.0d looks at whether there are significant gender differences for the children between the different groups. We thought at first that there may be a difference, since some parents may want their girls to grow up in their home culture, while for their boys, they would prefer the German environment since it may constitute a better working environment. But as Panel 2.0d shows, there seem to be no such differences.[15] Figure 2.2 then continues to contrast different characteristics, but there seem to be no relevant differences between the four groups. Panel 2.1a takes a closer look at the unemployment versus employment rates, Panel 2.1b looks at differences between marital status, Panel 2.1c contrasts the languages spoken at home, while Panel 2.1d graphs the different educational levels of the individuals. As already mentioned, there seem to be no significant differences between the fours groups in terms of these characteristics. So none of these characteristics should drive the differences between the intentions and the expectations in the following.

The next section provides the reader with the methodology used to infer the actual return based on the current information available to the individual.

2.4 Model

Let T be the duration until the return and let $\theta(t|x(t), x_0)$ be the hazard rate, which can be interpreted as the return rate or the return probability. Mathematically it can be represented as:

$$\theta(t, x(t), x_0) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt | T \geq t, x(t), x_0)}{dt} \tag{2.1}$$

t presents time since entry, $x(t)$ are time varying covariates, such as the current employment status, and the current family income, and x_0 are time invariant covariates, such as the age at migration, gender, education and country of origin.

The amount of money that migrants will earn in their home country and how the purchasing powers differ between the migrants country of origin and Germany builds the framework for the analysis between expectations and realizations. Information about what migrants wages would be in their home country is not available and GDP is used to infer how big the differences are between Germany and the sending country. Since the focus of the chapter is to explain differences between return intentions and return realizations, we need an expression for the

[15]With percent have gender kids, we are interested in families that have both a daughter and a son.

return realization which will be inferred through duration analysis. This analysis is said to be reduced form and we need to think about possible factors that migrants consider when forming expectations.

GDP is a good indicator to compare countries and as mentioned in the literature review the decision to return may be a part of the life-cycle, or the sending country may have caught up to the receiving country in terms of GDP. Comparing the GDP's of Germany and that of the sending countries, we know that either this did not happen, e.g., for countries such as Turkey, or Germany was just as good in terms of GDP as the sending country, e.g., France. In other words, a change in the arguments of the utility function changes the utility level. This can be modeled with the help of the duration analysis. To do so, first assume that the migrants to Germany are a homogeneous group, an assumption which may be relaxed in future work.

As emphasized above, the decision to return relies on the economic model which builds the framework for the hazard rate. As an example, for an individual to take the decision to move in 2005 it is needed that the expected present value of earnings proxied by GDP in the home country minus the moving costs are larger than the expected present value of earnings proxied by GDP in Germany. This formulation of the decision to move has been introduced by Sjaastad (1962). More formally, if one decides to move in 2005,

$$\sum_{t=2005}^{d} \frac{1}{(1+r)^t} \left(E[U(\mathrm{X}_T(t))] - E[U(\mathrm{X}_G(t))] \right) > c + \epsilon \tag{2.2}$$

has to hold. Where $X(t)$, are covariates that we control for, such as GDP, age at migration, marital status, family location ....[16] c represents the cost of moving, d is the expected year of death, r is the interest rate and ϵ is an error term. The subscript G stands for Germany, and the subscript T stands for Turkey.[17] This can be rewritten in terms of probabilities, such that:

$$\begin{aligned} &P(\text{move in 2005 from Germany to Turkey}) \qquad (2.3) \\ &\qquad = P\left(\epsilon < \sum_{t=2005}^{d} \frac{1}{(1+r)^t} \left(E[U(\mathrm{X}_T(t))] - E[U(\mathrm{X}_G(t))] \right) - c \right). \end{aligned}$$

[16]In the empirical specification part, we specify what covariates we control for.
[17]Turkey was chosen as an example, since as can be seen in Table 2.19 most migrants in the sample are from Turkey.

Which can be rewritten in terms of the hazard rate in 2005, such that:

$$\begin{aligned} & P\left(\epsilon < \sum_{t=2005}^{d} \frac{1}{(1+r)^t} \left(E[U(\mathrm{X}_T(t))] - E[U(\mathrm{X}_G(t))]\right) - c\right) \\ & = \Phi\left(\frac{\sum_{t=2005}^{d} \frac{1}{(1+r)^t} \left(E[U(\mathrm{X}_T(t))] - E[U(\mathrm{X}_G(t))]\right) - c}{\sigma_\epsilon}\right) \end{aligned} \tag{2.4}$$

Equation (2.5) is the expression of the hazard for 2005 and can easily be rewritten to get an expression for the hazard rate for each year.

Since we are ultimately interested in the expected duration of a stay, the duration framework allows us to write:

$$\begin{aligned} y(0) &= E(T|x_0, \text{expectations of future path of } x(t)) \\ &= \int_0^\infty \left[exp\left(-\int_0^\infty \theta(u|x(u), x_0)du\right)\right] dz \end{aligned} \tag{2.5}$$

in a continuous time framework. This equation can be rewritten for $y(t)$ where t can take any integer value in $[0, T]$ which means that we end up with possible $y(t)$, $y(t-1)$, $\ldots$, $y(0)$. This expression allows the individual to adapt her expectations. In other words, $y(0)$ may be different than $y(1)$ because individuals update the future path of $x(t)$. The model's predicted expectations will be compared to the respondents indicated intentions to see what drives the difference and whether people learn; are their predictions eventually converging to the "truth"?

Empirical Specification

Since the data at hand is of the discrete time format, the expected duration until the return is based on the assumption of a third order polynomial of time combined with a complementary log log model.[18] Then the full model specification is (assuming time invariant covariates):

$$cloglog[h(t, X)] = z_1 t + z_2 t^2 + z_3 t^3 + \beta X \tag{2.6}$$

[18] The third order polynomial is our preferred specification of the duration dependence, see Table 2.5 and the results section for more details.

where X represents socio-economic characteristics.[19] In other words, the hazard can be rewritten as:

$$h(t, X) = 1 - exp[-exp(z_1 t + z_2 t^2 + z_3 t^3 + \beta X)] \tag{2.7}$$

where z_1, z_2, z_3 are estimated together with the intercept and the slope parameters within the vector β. Survival up to the end of the j$^{\text{th}}$ interval (or completion of the j$^{\text{th}}$ cycle) is given by:

$$S(j) = S_j = \prod_{k=1}^{j} (1 - h_k) \tag{2.8}$$

where h_k is the cloglog function of characteristics.

For each individual, we calculate the expected duration of the stay at the moment of the interview. Thus even if the interview happens when a person has already spent 10 years in Germany, we calculate the expected duration of the stay from that point onwards. Therefore we consider the year of the interview as $t = 0$. Consider now the case where people form their expectations based on the current GDP only, and all other variables included in the model so far do not vary with time or only vary once - marital status, employed, family at home, spouse at home. Age at migration and attended school in Germany are time invariant covariates. Hence the predicted return in the discrete time framework is given by,

$$E[T] = \sum_{k=1}^{K} S(t) = S(1) + S(2) + S(3) + \ldots + S(K) \tag{2.9}$$

where K is the maximum survival time.[20] The predicted return can be rewritten as:

$$E[T] = (1 - h_1) + (1 - h_1)(1 - h_2) + \ldots + (1 - h_1)(1 - h_2)(1 - h_3) \ldots (1 - h_K) \tag{2.10}$$

where h_x represent the hazard at time x.[21] In the following the predicted return will be denoted by $E[T]$ while the intended duration will be denoted by $\tilde{E}[T]$. The next subsection discusses the results for this model and explains the sample selection criteria.

[19]We control for sex, age at migration, difference in GDP between Germany and the source country, marital status, whether or not the individual attended school in Germany, whether or not the individual has family at home and whether or not the individual's spouse is at home. Furthermore we control for the country of origin.

[20]In the empirical part we assume that the maximum survival time equals the expected lifetime duration, approximated by 100 − current age.

[21]As an example:

$$h_1(t, X) = 1 - exp[-exp(z_1 t + z_2 t^2 + z_3 t^3 + \beta X)]$$
$$h_2(t+1, X) = 1 - exp[-exp(z_1(t+1) + z_2(t+1)^2 + z_3(t+1)^3 + \beta X)]$$
$$h_3(t+2, X) = 1 - exp[-exp(z_1(t+2) + z_2(t+2)^2 + z_3(t+2)^3 + \beta X)]$$

2.5 Results

As shortly mentioned in the data section, we consider only migrants that are already in Germany and present in the SOEP. Furthermore we consider adults, who are older than 18 years in order to include those individuals that take the return decision themselves. As the use of the GDP Data from Angus Maddison forced the drop of the year 2009, we are left with 25 years for the analysis (1984-2008) and 3152 individuals, where 574 durations until re-migration are not right censored.

Tables 2.5 and 2.6 show the results of the complementary log log model, and logit model which are the underlying models for the predicted return. These specifications allow the construction of the predicted return as stated in the methodology section. The estimates are shown to provide evidence that all the coefficients point in the right direction. As an example, being employed makes you less likely to return, while having your spouse in the your home country makes you more likely to return. Males also seem to be less likely to return than females. Compared to singles every other marital status type is less likely to return. Whether the logit model or the complementary clog log specification is used, does not change these effects.

Furthermore Table 2.5 as well as Table 2.6 test which duration specification may be the best. In both tables, Column (1) includes year dummies, in order to give a fully nonparametric specification of the duration dependence, while Column (5) includes time interval dummies, allowing for a piecewise constant specification of the duration dependence. We also checked the discrete-time analogue of the continuous time Weibull model ($ln(t)$) as well as a fifth order polynomial in time and a third order polynomial in time.

Our preferred specification is the third order polynomial, which also fits the pattern that at the beginning the individual may be more likely to return, while the likelihood to return decreases until the individual reaches the retirement age, where the likelihood increases again. These specifications, as explained in the methodology section, allow us to “extract” the hazard rate which allow the construction of the predicted return. All predicted returns analyzed below are based on the complementary log log model with a third order polynomial in time to model the duration dependence.

Before analyzing the differences between the intentions and the predicted return, let us look at the individuals intentions and what are driving factors of the changes in these intentions.

Table 2.5: Complementary Log-log model

	(1)	(2)	(3)	(4)	(5)
Male	-0.146	-0.148	-0.143	-0.143	-0.145
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Age at Migration	-0.00390	-0.00510	-0.00332	-0.00335	-0.00687
	(0.00692)	(0.00652)	(0.00691)	(0.00693)	(0.00672)
$\ln(GDP_G)$-$\ln(GDP_H)$	0.00845	0.0102	0.0131	0.0130	0.00609
	(0.0547)	(0.0546)	(0.0547)	(0.0547)	(0.0545)
Married	-0.646***	-0.590***	-0.643***	-0.642***	-0.552***
	(0.144)	(0.121)	(0.142)	(0.143)	(0.132)
Married living separated	-0.565	-0.464	-0.544	-0.543	-0.441
	(0.389)	(0.377)	(0.387)	(0.387)	(0.381)
Divorced	-1.097***	-1.039***	-1.098***	-1.096***	-0.965**
	(0.405)	(0.394)	(0.404)	(0.405)	(0.398)
Widowed	-1.115***	-1.064***	-1.136***	-1.135***	-1.002***
	(0.389)	(0.374)	(0.388)	(0.389)	(0.381)
Employed	-0.691***	-0.694***	-0.674***	-0.674***	-0.681***
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
Family at Home	0.0289	-0.00108	-0.00941	-0.00973	-0.0343
	(0.198)	(0.197)	(0.198)	(0.198)	(0.197)
Spouse at Home	1.095***	1.127***	1.120***	1.120***	1.103***
	(0.190)	(0.189)	(0.189)	(0.189)	(0.189)
Attended School in Germany	-0.142	-0.169	-0.150	-0.150	-0.155
	(0.287)	(0.286)	(0.286)	(0.286)	(0.286)
GDP_G Growth	0.0234	0.0232	0.0259	0.0259	0.0202
	(0.0284)	(0.0282)	(0.0283)	(0.0283)	(0.0284)
GDP_H Growth	0.0242**	0.0274**	0.0262**	0.0262**	0.0255**
	(0.0115)	(0.0119)	(0.0118)	(0.0118)	(0.0116)
GDP_G Growth Imy	-0.00894**	-0.00764***	-0.00849**	-0.00852**	-0.00641**
	(0.00350)	(0.00247)	(0.00338)	(0.00342)	(0.00287)
GDP_H Growth Imy	0.00410***	0.00406***	0.00396***	0.00397***	0.00420***
	(0.000845)	(0.000797)	(0.000828)	(0.000831)	(0.000828)
Income	0.0000748	0.0000768	0.0000753	0.0000753	0.0000723
	(0.0000593)	(0.0000588)	(0.0000591)	(0.0000591)	(0.0000592)
Aged 60 or older	1.035***	1.064***	1.022***	1.023***	1.105***
	(0.173)	(0.166)	(0.172)	(0.173)	(0.169)
ln(t)		-0.484***			
		(0.129)			
Time in Germany			-0.192***	-0.196**	
			(0.0480)	(0.0865)	
Time in Germany^2			0.00742***	0.00774	
			(0.00240)	(0.00623)	
Time in Germany^3			-0.0000922***	-0.000100	
			(0.0000339)	(0.000145)	
Time in Germany^5				1.31e-09	
				(2.36e-08)	
Constant	-20.01	-3.630***	-3.526***	-3.512***	
	(723.6)	(0.432)	(0.402)	(0.471)	
Year Dummies	Yes	No	No	No	No
Country Region	Yes	Yes	Yes	Yes	Yes
Time Interval Dummies	No	No	No	No	Yes
Observations	32200	32200	32200	32200	32200

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the dummy variable whether a person leaves or not.

Table 2.6: Logit model

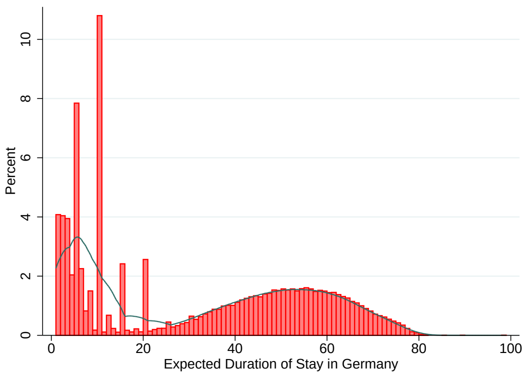
	(1)	(2)	(3)	(4)	(5)
Male	-0.147	-0.148	-0.143	-0.143	-0.145
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Age at Migration	-0.00379	-0.00503	-0.00323	-0.00328	-0.00684
	(0.00708)	(0.00664)	(0.00704)	(0.00707)	(0.00687)
$\ln(GDP_G)-\ln(GDP_H)$	0.00820	0.0109	0.0133	0.0132	0.00580
	(0.0559)	(0.0555)	(0.0557)	(0.0557)	(0.0556)
Married	-0.660***	-0.598***	-0.653***	-0.652***	-0.559***
	(0.146)	(0.123)	(0.144)	(0.145)	(0.134)
Married living separated	-0.575	-0.461	-0.541	-0.539	-0.444
	(0.402)	(0.389)	(0.399)	(0.399)	(0.393)
Divorced	-1.115***	-1.055***	-1.114***	-1.112***	-0.978**
	(0.411)	(0.398)	(0.408)	(0.409)	(0.402)
Widowed	-1.142***	-1.081***	-1.155***	-1.153***	-1.019***
	(0.395)	(0.379)	(0.393)	(0.393)	(0.386)
Employed	-0.704***	-0.705***	-0.685***	-0.685***	-0.694***
	(0.159)	(0.158)	(0.159)	(0.159)	(0.159)
Family at Home	0.0263	-0.00243	-0.0106	-0.0111	-0.0365
	(0.201)	(0.200)	(0.201)	(0.201)	(0.200)
Spouse at Home	1.144***	1.162***	1.156***	1.155***	1.144***
	(0.199)	(0.197)	(0.197)	(0.197)	(0.197)
Attended School in Germany	-0.142	-0.172	-0.154	-0.154	-0.160
	(0.292)	(0.290)	(0.291)	(0.291)	(0.290)
GDP_G Growth	0.0237	0.0233	0.0261	0.0261	0.0200
	(0.0293)	(0.0289)	(0.0291)	(0.0291)	(0.0292)
GDP_H Growth	0.0248**	0.0280**	0.0268**	0.0268**	0.0260**
	(0.0120)	(0.0123)	(0.0122)	(0.0122)	(0.0120)
GDP_G Growth Imy	-0.00918**	-0.00776***	-0.00862**	-0.00866**	-0.00647**
	(0.00358)	(0.00251)	(0.00344)	(0.00347)	(0.00291)
GDP_H Growth Imy	0.00416***	0.00414***	0.00403***	0.00404***	0.00429***
	(0.000866)	(0.000815)	(0.000847)	(0.000850)	(0.000847)
Income	0.0000760	0.0000780	0.0000765	0.0000764	0.0000739
	(0.0000599)	(0.0000594)	(0.0000597)	(0.0000597)	(0.0000597)
Aged 60 or older	1.053***	1.080***	1.038***	1.040***	1.124***
	(0.176)	(0.169)	(0.175)	(0.175)	(0.172)
ln(t)		-0.495***			
		(0.132)			
Time in Germany			-0.196***	-0.203**	
			(0.0492)	(0.0885)	
Time in Germany^2			0.00761***	0.00814	
			(0.00245)	(0.00636)	
Time in Germany^3			-0.0000946***	-0.000108	
			(0.0000347)	(0.000147)	
Time in Germany^5				2.16e-09	
				(2.39e-08)	
Constant	-19.40	-3.607***	-3.498***	-3.475***	
	(679.1)	(0.441)	(0.412)	(0.483)	
Year Dummies	Yes	No	No	No	No
Country Region	Yes	Yes	Yes	Yes	Yes
Time Interval Dummies	No	No	No	No	Yes
Observations	32200	32200	32200	32200	32200

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the dummy variable whether a person leaves or not.

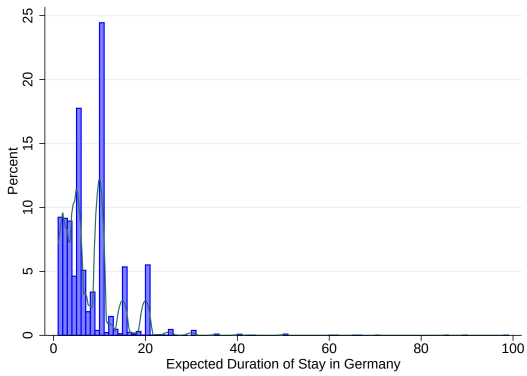
Figure 2.3 plots the intended duration of stay, in Panel a) we imputed the intended duration for those who wanted to stay forever as 100 − their current age, while in Panel b) we only take a look at those that actually tell us how long they plan on staying. In both panels we see that the individuals show bunching behavior around 5, 10, 15, 20 years. This bunching may already point towards a simplifying heuristic, when individuals form their intentions.

Figure 2.3: Expected Duration of Stay

(a) Intended Duration of Stay for those who intend to stay forever = 100 - current age



(b) Intended Duration of Stay without those who intend to stay forever



Tables 2.7 and 2.8 look at the driving factors behind the changes in peoples return intentions. We take the first difference in their intentions - as an example we compute $\tilde{E}[2006] - \tilde{E}[2005]$ - and regress these changes in their intentions on the changes in their socio-economic changes: e.g., employed_{2006} - employed_{2005}. All regressions include individual fixed effects and the standard errors are clustered at the individual level. What seems to be a driving factor in these adjustments is whether there is a change in your life satisfaction, meaning that if you are more satisfied in one year than in the following (happiness variable), it influences your intention to return. This finding is as expected, since an increase in life satisfaction may also reduce the psychic costs that occur from migration. Other variables that seem to have significant effects on these changes are attended school in Germany variable and the differences in GDP variable.

Table 2.8 takes a closer look at some of the behavioral factors contained in the SOEP and how they influence the changes in the individuals intentions. Unfortunately the number of observations decreases substantially depending on which variables are included. Data on control over life is only available in years 1994-1996, 1999 and 2005, data on remitting is only available in the years 1984-1993 and 1995, while data on risk preferences is only available in the years 2006-

Table 2.7: Difference in Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(GDP_G)$-$\ln(GDP_H)$ FD	-1.35*	-1.35*	-1.48*	-2.10**	-1.21	-1.88**
	(0.82)	(0.82)	(0.82)	(0.82)	(0.83)	(0.83)
Employed FD	0.22*	0.22*	0.21	0.25*	0.20	0.19
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Income FD	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Family at Home FD	-0.02	-0.09	-0.11	-0.06	-0.05	-0.14
	(0.49)	(0.50)	(0.50)	(0.49)	(0.46)	(0.51)
Spouse at Home FD	-0.29	-0.29	-0.29	-0.31	-0.40	-0.43
	(0.41)	(0.41)	(0.41)	(0.46)	(0.44)	(0.44)
Attended School in Germany FD	-0.12	-0.12	-0.54**	-0.28*	0.22	-0.55**
	(0.25)	(0.25)	(0.26)	(0.16)	(0.24)	(0.22)
Happiness FD	0.10***	0.10***	0.10***	0.09***	0.09***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Have Children FD	0.42	0.42	0.22			-0.27
	(0.81)	(0.81)	(0.81)			(0.61)
Death of Mother FD		1.52				
		(1.15)				
Death of Father FD		-1.20				
		(0.86)				
Aged 60 or older			0.38***			0.49***
			(0.11)			(0.12)
Time in Germany			-0.04***			-0.06***
			(0.01)			(0.01)
Married				-0.45***		
				(0.10)		
Married living separated				-0.52		
				(0.37)		
Divorced				-0.24		
				(0.40)		
Widowed				-0.43*		
				(0.26)		
Finished Higher Education					-0.59	
					(0.48)	
Finished School					0.79	
					(0.78)	
vocational					-1.14	
					(0.74)	
Married FD						-0.15
						(0.25)
Married living separated FD						-0.07
						(0.72)
Divorced FD						-0.04
						(0.82)
Widowed FD						-0.06
						(0.29)
Constant	-0.13***	-0.13***	0.72***	0.00	-0.02	1.04***
	(0.01)	(0.01)	(0.16)	(0.03)	(0.06)	(0.18)
Number of Clusters	1858	1858	1858	1692	1783	1593
Observations	11219	11219	11219	10502	10867	9555
R^2	0.10	0.10	0.10	0.10	0.10	0.12

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Clustered standard errors in parentheses. The dependent variable is the change of the expected duration of stay. All regressions include individual fixed effects.

2009.[22] Column (1) is the baseline specification without behavioral factors, in order to make it easier for the reader to see what happens to the sample size when the other variables are included. Another unfortunate side-effect of the small sample size is that none of the behavioral coefficients are significant, which does not leave much room for argumentation.

Last but not least, let us move to the forecast errors. Figure 2.4 plots the difference between the intentions and the predicted return. Again Panel a) plots the difference for the whole sample, where for those that intended to stay forever we imputed their maximal survival time as 100 − their current age. Panel b) plots the difference for the reduced sample, where we leave those out that intend to stay forever. A quick glance at Panel a) gives us hope, that there seem to be many people predicting the duration of their stay correctly, but when we take those out that intend to stay forever (for whom we imposed how long they remain in Germany, Panel b)) practically no remaining individual has a correct prediction. Figure 2.4b) shows that individuals overestimate the return to their home country, equivalently stated, underestimate their time spent in Germany. When looking at the difference, the intended return is constantly below the actual predicted return, which makes the difference negative. This is an important finding and may point toward overconfidence; a topic very nicely introduced in Kahneman (2011). In the current work, overconfidence would have to go along with net attachment in the sense that individuals are overconfident about the fact that they will be true to their family (to their "roots") and want to return home, and thus underestimate their attachment to Germany. More importantly though the finding of the overestimation of the probabilities to return is along the lines of Rabin (2002). He models the belief in the "Law of Small Numbers", where people exaggerate the degree to which small samples resemble the population from which they are drawn.

A further thing we look at, is whether "narrow framing" plays a role. We use the term "narrow framing" to define the fact that people may only look at shorter time intervals than their whole lives. Trying to predict what will happen in 40 years from now is hard, and therefore it may also be hard to predict what one will do in 40 years concerning the return migration. Therefore we take a look at people's predictions if we make a cut off at e.g., 10 years and everyone that states that they want to remain longer than 10 years, we re-coded as only wanting to stay 10 years.[23]

[22] To get a little more observations, we fill the variables forward using stata's stfill command. This means that the variable takes on the last value until a change in the variable happens. This assumption should not change any of our results.

[23] We played around with these numbers, and 10 just gave the best predictions, which is why we stick to that number.

Table 2.8: Difference in Expectations Behavioral Factors

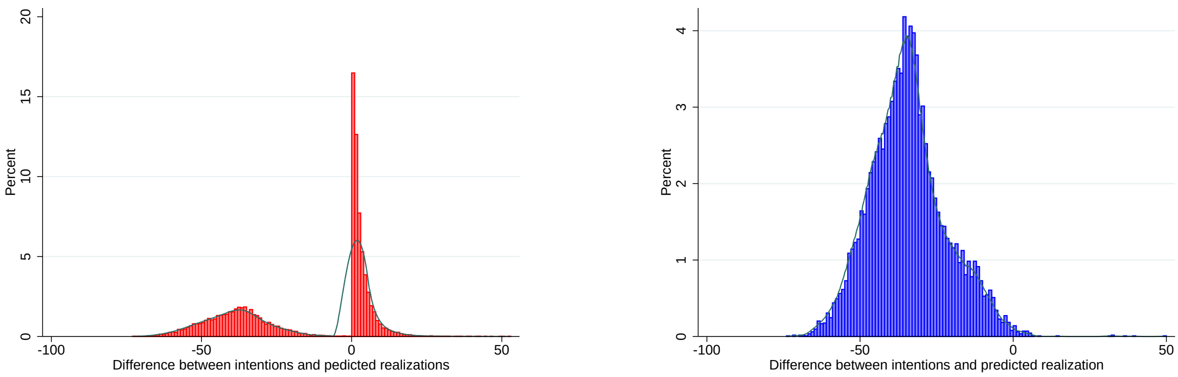
	(1)	(2)	(3)	(4)	(5)
$\ln(GDP_G)$-$\ln(GDP_H)$ FD	-1.88**	0.11	-1.46*	5.03	58.51
	(0.83)	(1.73)	(0.83)	(6.50)	(43.15)
Employed FD	0.19	0.01	0.21	0.07	-0.29
	(0.13)	(0.20)	(0.14)	(0.55)	(0.41)
Income FD	-0.00*	-0.00	-0.00	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spouse at Home FD	-0.43		-0.29		
	(0.44)		(0.41)		
Family at Home FD	-0.13				
	(0.50)				
Attended School in Germany FD	-0.62***				
	(0.17)				
Happiness FD	0.10***	-0.00	0.10***	-0.12	0.04
	(0.03)	(0.07)	(0.03)	(0.23)	(0.14)
Aged 60 or older	0.49***	0.18	0.39***	0.51	0.25
	(0.12)	(0.21)	(0.11)	(1.08)	(1.10)
Time in Germany	-0.06***	-0.01	-0.04***	0.05	-0.01
	(0.01)	(0.02)	(0.01)	(0.20)	(0.24)
Married FD	-0.15	0.00		0.59	-0.31
	(0.25)	(0.31)		(1.46)	(2.50)
Married living separated FD	-0.07	0.00		1.09	0.41
	(0.72)	(0.79)		(1.72)	(2.56)
Divorced FD	-0.03	0.01		-0.29	-0.77
	(0.82)	(0.93)		(1.53)	(2.30)
Widowed FD	-0.06	-0.31			
	(0.29)	(0.38)			
Control Over Life		0.18			
		(0.36)			
Remitting			-0.15		
			(0.14)		
Medium low risktaker				-0.15	
				(0.55)	
Medium high risktaker				-0.24	
				(0.82)	
High risktaker				-0.94	
				(0.70)	
Risktaker FD					-0.14
					(0.44)
Constant	1.03***	-0.29	0.81***	-1.50	1.06
	(0.18)	(0.66)	(0.18)	(5.30)	(6.78)
Number of Clusters	1593	723	1713	339	299
Observations	9555	3068	10798	901	700
R^2	0.12	0.12	0.09	0.12	0.34

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Clustered standard errors in parentheses. The dependent variable is the change of the expected duration of stay. All regressions include individual fixed effects. Data on control over life is only available in years 1994-1996, 1999 and 2005. Data on remitting is only available in years 1984-1992, 1993 and 1995. Data on risk preferences is only available in years 2006-2009.

Figure 2.4: Difference Between Intentions and Predicted Realizations

(a) Those who intend to stay forever maximal survival time = 100 - current age

(b) Without those who intend to stay forever



The top panel of Figure 2.5 looks at the intended duration of stay, once we restrict the window for predictions to 10 years. Panel a) includes those that intend to stay forever (coded as intending to stay for 10 more years), while Panel b) excludes these individuals. The lower panel of Figure 2.5 takes a look at the difference between the narrowly framed intention and the predicted return of this model. In Panel c), close to 70% of the individuals now predict their stay correctly, but again taking those out that intend to stay forever, only 35% of the individuals seem to correctly predict the length of their stay within this framework. Nevertheless it is important to notice that in Figure 2.4 Panel b) nearly nobody predicted the length of their stay correctly. These results point towards the fact that not just overconfidence may play a role, but also the forecasting ability of the individuals. It is easier to give a response to what you may be doing in a year or two than to give a response to the question about when you may want to return. For the rest of the chapter we go back to the initial specification of the predicted return, where the sum is taken until the expected survival time, which is approximated by 100 - the current age of the individual.

Another important question when looking at these graphs is whether people learn from their “past” behavior. In other words; is the difference between their intentions and the predicted realization approaching zero the longer they stay in Germany? Figure 2.6 tries to take a closer look at this learning problem by looking at the changes over time spent in Germany. Looking at the different panels, it seems that people do not learn to predict their preferences more accurately the longer they are in Germany. The distribution shifts a little bit closer to zero which may be due to the fact that the population gets older.

Figure 2.5: "Narrow Framing"

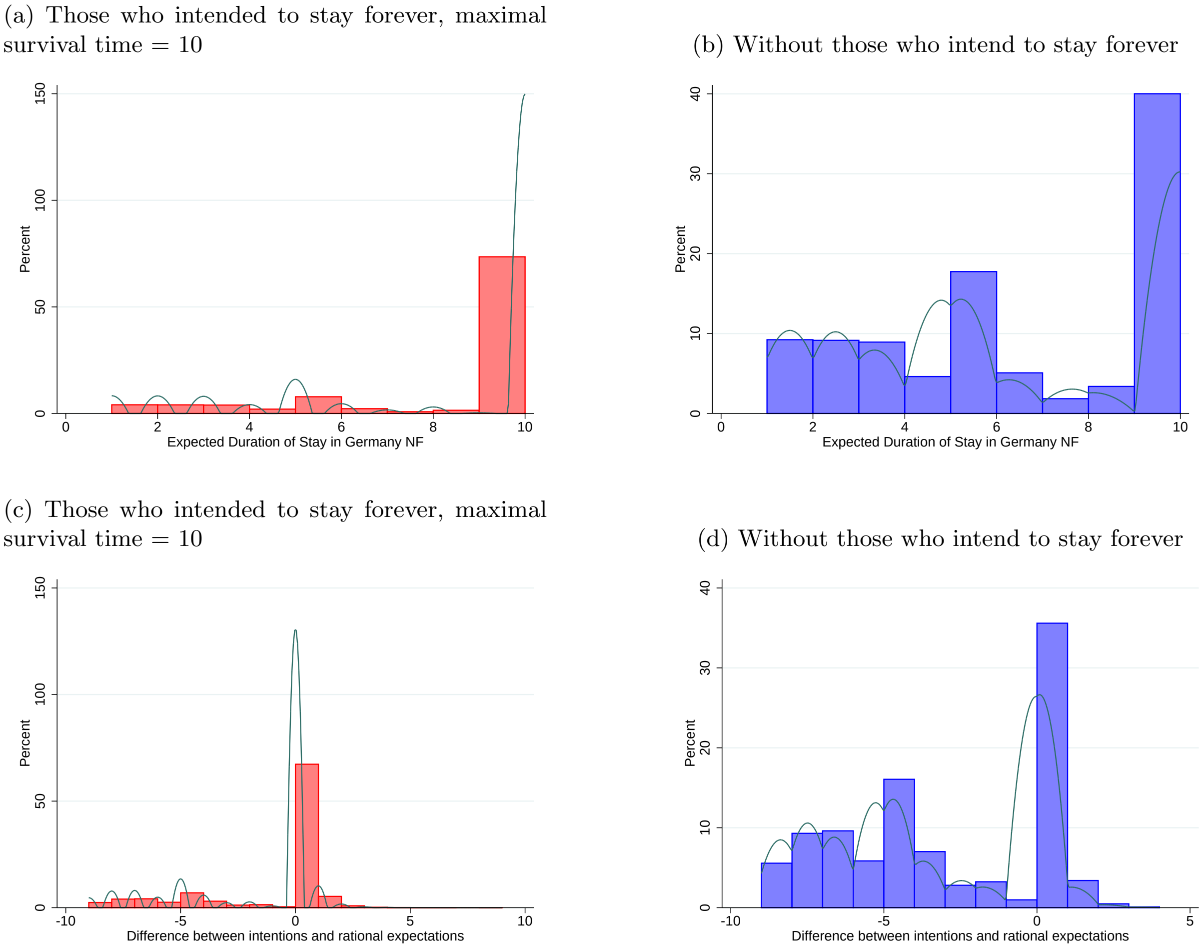
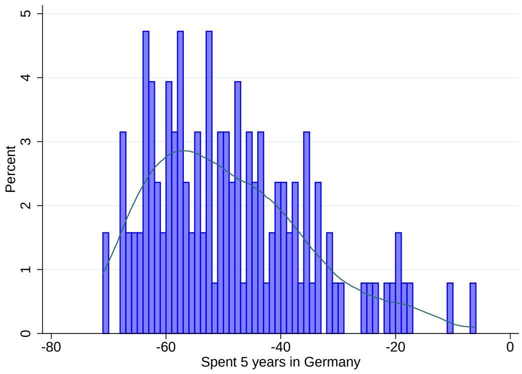
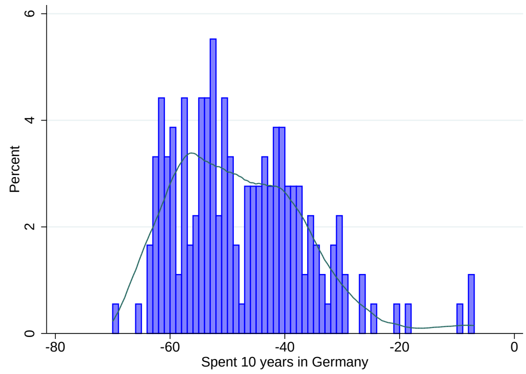


Figure 2.6: Difference Between Intentions and Predicted Return, Learning?

(a) Spent 5 years in Germany



(b) Spent 10 years in Germany



(c) Spent 15 years in Germany

(d) Spent 20 years in Germany

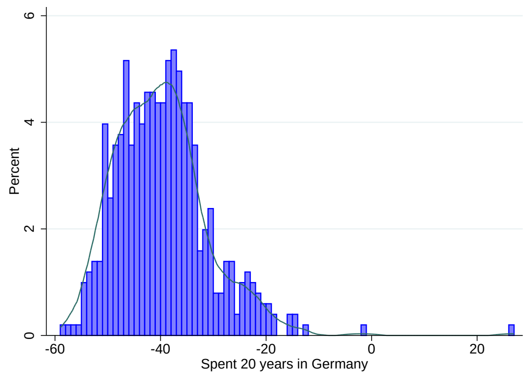


Figure 2.7 then plots the average forecast error (equivalent to the average difference) over different time specifications. Panel a) plots the average forecast error over time spent in Germany, and what was not obvious before now seems to become relevant. It seems that the longer people are in Germany, the more accurate they get on average. The largest error that they make is when they have spent 20 years in Germany, while their error is practically zero once they have spent 60 years in Germany. This could go along with the fact that having spent 20 years in a country you may still believe that you eventually return, but the older you get, the better you are at comparing your actual chance of leaving and so you seem to be more accurate with your forecast.

Panel b) helps us explain at what age you seem to get better at predicting your utility or your future choice variables. Toward this end, there is a clear direction; the older you get, the better you get at predicting your remaining duration. This finding is not too surprising as the older one is, the shorter the remaining horizon gets, and therefore one may also be better at predicting the duration of the stay.

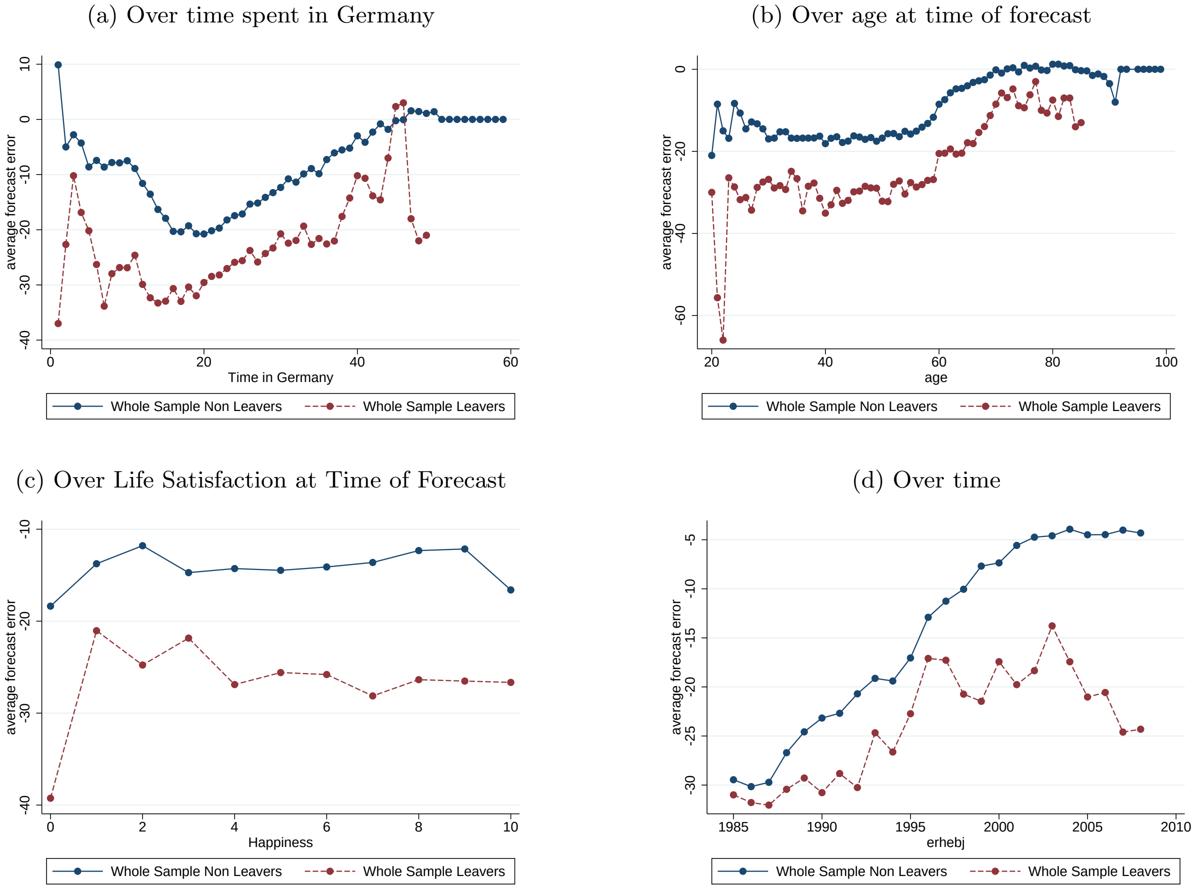
Panel c) plots the average forecast error over the different life satisfaction possibilities, where 0 stands for not satisfied, while a 10 ranks you at very satisfied. We show this graph, since happiness seemed to explain some of the changes in the intended returns, but how satisfied you are with your current life does not seem to have a different effect on the average forecast error.

Panel d) plots the average forecast error over time. The increasing slope does not make too much sense to us, except that the individuals that we consider in the sample may get older and as already stated above then get better at forecasting their own preferences. Nevertheless it is useful to include this graph, in order to show that there are no relevant macro shocks that drive our results.

Tables 2.9, 2.10, 2.11 and 2.12 finally take a closer look at the differences between the intentions and the predicted return. In Table 2.9, Columns (2), (4) and (5) include individual fixed effects, where the standard errors are clustered at the individual level. The OLS results, are shown for comparison, since we are in a panel data set up, we need to include individual fixed effects and also cluster the standard errors.[24] As an example, one can see the effect when taking a closer look at attended school in Germany. The coefficient changes sign and magnitude as soon as we

[24] The identification with the use of individual fixed effects is driven by variations across time by each individual. Since many of the variables included in the regression may be time invariant, we included the yearly OLS results in the appendix in Tables 2.20 and 2.21.

Figure 2.7: Average Forecast Error



include individual fixed effects and clustering. A further thing to note, is that the coefficient estimate on time spent in Germany are all significant and point into the right direction. The longer one has been in Germany, the smaller the difference between the intentions and the predicted return. The coefficient on the above 60 dummy is also highly significant, showing that it is very important to control for this hump at the retirement age. The coefficient on the above 60 dummy is positive, but since the difference is always negative, this means that the difference decreases as soon as one is above 60. The coefficient on the disadvantage due to origin variable is also significant at the 1% level, and is negative. This implies, again as the difference is on average negative, that those individuals that feel a disadvantage, understimate the duration of their stay by more than those that do not feel disadvantaged. Having attended school in Germany is one of the surprising coefficients since it increases the difference when we focus on the specifications that include individual fixed effects in Table 2.9 Columns (3), (5) and (6).

Table 2.10 and 2.11 are robustness checks of the results from Table 2.9. Table 2.10 is a first test on the sign and the magnitude of the results of table 2.9, as we exclude those observations where individuals indicate that they intend to stay forever. For Table 2.11 we split the sample randomly in half, where for one half of the sample the hazard model was estimated while for the other half, the average forecast error was predicted using the results from the hazard model.

Table 2.12 includes the behavioral factors where we take a look at the whole sample, but as before we lose power, due to a decrease in the number of observations. Here the interesting behavioral results come from whether or net a person has remitted and again the locus of control variable. If an individual has been paying remittances, she is underestimating the time she is going to spent in Germany. The coefficient is negative, but again as the difference is always negative, this means that in absolute terms the difference becomes larger. On the other hand, if an individual has control over her life, she will be better at giving an estimate of her duration of stay. The coefficient is positive, indicating that the difference becomes smaller.

2.6 Conclusion

This chapter shows evidence of a difference between expectations and realizations of the duration of the stay in the host country. Unfortunately we are not able to show whether there is projection bias, due to data restrictions, but we show that predictions get better the longer the individual stayed in Germany. The main rationale behind this finding, in our opinion, is that the individuals'

Table 2.9: Difference between the Intentions and the predicted Return

	(1)	(2)	(3)	(4)	(5)	(6)
Male	-0.92***	-0.14		-0.44		
	(0.30)	(0.32)		(0.32)		
Age at Migration	0.25***	0.21***		0.14***		
	(0.02)	(0.02)		(0.02)		
$\ln(GDP_G)-\ln(GDP_H)$	-1.31	-17.97***	-4.75	-6.18	-4.90	-5.04
	(2.62)	(3.69)	(3.63)	(23.26)	(3.69)	(3.68)
$\ln(GDP(t-1)_G)-\ln(GDP(t-1)_H)$	19.30***	18.34***	13.23***	13.55	13.84***	13.94***
	(4.29)	(5.67)	(4.30)	(23.68)	(4.54)	(4.54)
$\ln(GDP(t-2)_G)-\ln(GDP(t-2)_H)$	-16.71***	1.28	-6.25*	-8.03	-6.37*	-6.51*
	(2.66)	(3.58)	(3.27)	(6.02)	(3.45)	(3.45)
Married	13.56***	-4.43***	-2.45	-4.34***	-1.41	-1.36
	(0.31)	(0.80)	(2.15)	(0.82)	(2.34)	(2.33)
Married living separated	13.71***	-3.77***	-1.99	-4.29***	-0.92	-0.77
	(1.14)	(1.29)	(2.46)	(1.30)	(2.71)	(2.72)
Divorced	16.29***	-1.88*	-4.09*	-2.64***	-2.70	-2.57
	(0.75)	(1.00)	(2.13)	(1.01)	(2.45)	(2.44)
Widowed	12.42***	-4.66***	-3.83*	-4.90***	-2.33	-2.12
	(0.85)	(1.10)	(2.30)	(1.13)	(2.49)	(2.49)
Employed	-0.48*	-0.60*	-0.82*	-1.92***	-0.92*	-0.88*
	(0.28)	(0.33)	(0.47)	(0.34)	(0.49)	(0.51)
Family at Home	7.46***	3.46***	7.29	2.77***	5.97	6.00
	(0.40)	(0.37)	(6.43)	(0.38)	(5.85)	(5.83)
Spouse at Home	1.46*	-3.65**		-1.24		
	(0.85)	(1.48)		(1.53)		
Attended School in Germany	3.53***	1.28	-25.28***	0.82	-25.17***	-25.35***
	(0.68)	(0.83)	(0.99)	(0.83)	(1.06)	(1.09)
Time in Germany	-0.88***	0.44***	-0.67*	-0.11	-0.64*	-0.63*
	(0.13)	(0.15)	(0.34)	(0.17)	(0.36)	(0.36)
Time in Germany^2	0.03***	-0.05***	0.03**	-0.01	0.03*	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Time in Germany^3	-0.00***	0.00***	-0.00*	0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Children?	-0.98***	1.52***	-3.08	1.24***	-3.41	-3.54
	(0.32)	(0.40)	(2.49)	(0.40)	(2.40)	(2.40)
Aged 60 or older	4.07***	2.46***	3.76***	3.19***	3.55***	3.48***
	(0.47)	(0.54)	(0.69)	(0.55)	(0.73)	(0.73)
Writing German?		3.27***	0.45	-0.07	0.61	0.63
		(0.45)	(0.78)	(0.51)	(0.86)	(0.86)
Speaking German?		3.07***	-0.42	1.39	-0.62	-0.62
		(1.06)	(1.88)	(1.32)	(2.59)	(2.60)
Disadvantage due to origin?				-1.42***	-0.78**	-0.75**
				(0.30)	(0.38)	(0.37)
Language Newspaper German?				5.78***	0.93	0.93
				(0.41)	(0.69)	(0.69)
Income						-0.00
						(0.00)
Happiness						0.21**
						(0.09)
Constant	-26.87***	-19.66***	-5.46	-16.94***	-9.90	-11.14
	(1.09)	(1.65)	(7.57)	(3.45)	(7.89)	(7.93)
Country Region	No	No	No	Yes	No	No
Bundesland FE	No	No	No	Yes	Yes	Yes
R^2	0.20	0.11	0.68	0.18	0.68	0.68
Number of Clusters			2075		1950	1950
Observations	26603	13258	13258	12336	12336	12336

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the predicted realization. The columns that include the number of clusters, include individual fixed effects and those standard errors are clustered.

Table 2.10: Difference without those that intend to stay forever

	(1)	(2)	(3)	(4)	(5)
Male	-0.56**		-0.53*		
	(0.27)		(0.28)		
Age at Migration	0.69***		0.65***		
	(0.02)		(0.02)		
$\ln(GDP_G)-\ln(GDP_H)$	-5.81*	-7.70***	-9.36***	-7.98***	-7.94***
	(3.04)	(2.23)	(3.07)	(2.28)	(2.27)
$\ln(GDP(t-1)_G)-\ln(GDP(t-1)_H)$	7.12	4.26**	6.74	4.93**	4.96**
	(4.37)	(2.05)	(4.36)	(2.06)	(2.06)
$\ln(GDP(t-2)_G)-\ln(GDP(t-2)_H)$	-0.94	2.91	2.65	1.54	1.54
	(3.05)	(3.03)	(3.16)	(2.58)	(2.58)
Married	-6.18***	-6.79	-4.93***	-7.97*	-8.01*
	(0.63)	(4.72)	(0.67)	(4.68)	(4.64)
Married living separated	-3.24***	-7.22*	-2.91***	-8.28*	-8.31*
	(1.06)	(4.25)	(1.08)	(4.30)	(4.27)
Divorced	-7.60***	-9.18**	-5.79***	-10.75**	-10.88**
	(0.89)	(4.46)	(0.91)	(4.63)	(4.63)
Widowed	-6.51***	-8.09*	-6.88***	-9.50**	-9.66**
	(0.94)	(4.53)	(1.00)	(4.73)	(4.72)
Employed	-0.03	-1.40***	-0.80***	-1.54***	-1.71***
	(0.27)	(0.31)	(0.28)	(0.32)	(0.40)
Family at Home	0.62	-0.47	1.07**	-0.74	-0.80
	(0.45)	(1.26)	(0.51)	(1.35)	(1.40)
Spouse at Home	2.83***		4.09***		
	(0.85)		(0.89)		
Attended School in Germany	-1.91***	-2.40***	-1.77**	-2.44***	-2.64***
	(0.72)	(0.55)	(0.70)	(0.56)	(0.60)
Time in Germany	1.25***	0.98**	1.39***	1.19***	1.17***
	(0.16)	(0.40)	(0.16)	(0.43)	(0.43)
Time in Germany^2	-0.02**	-0.01	-0.02***	-0.02	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Time in Germany^3	0.00**	0.00	0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Children?	-0.41	-3.60	-0.24	-3.65	-3.53
	(0.32)	(2.78)	(0.33)	(2.81)	(2.80)
Aged 60 or older	2.87***	3.78***	3.42***	3.70***	3.76***
	(0.40)	(0.56)	(0.42)	(0.61)	(0.62)
Writing German?	1.48***	-0.40	0.60*	-0.39	-0.39
	(0.31)	(0.34)	(0.33)	(0.36)	(0.35)
Speaking German?	0.19	-0.33	0.53	-0.46	-0.50
	(0.72)	(0.64)	(0.86)	(0.81)	(0.82)
Disadvantage due to origin?			-0.59**	-0.06	-0.10
			(0.25)	(0.28)	(0.29)
Language Newspaper German?			1.36***	0.38	0.37
			(0.28)	(0.43)	(0.42)
Income					0.00
					(0.00)
Happiness					-0.16**
					(0.08)
Constant	-74.04***	-43.61***	-77.16***	-42.43***	-41.14***
	(1.45)	(9.20)	(1.86)	(9.87)	(9.81)
Country Region	No	No	Yes	No	No
Bundesland FE	No	No	Yes	Yes	Yes
R^2	0.69	0.91	0.72	0.91	0.91
Number of Clusters		760		705	705
Observations	3133	3133	2883	2883	2883

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the predicted realization without those that intend to stay forever. The columns that include the number of clusters, include individual fixed effects and those standard errors are clustered.

Table 2.11: Robustness Check on the Difference

	(1)	(2)	(3)	(4)	(5)
Male	-1.07***		-1.34***		
	(0.41)		(0.42)		
Age at Migration	0.14***		0.09***		
	(0.03)		(0.03)		
$\ln(GDP_G)$-$\ln(GDP_H)$	-7.17	10.14**	-0.18	10.05**	10.04**
	(4.89)	(4.81)	(4.93)	(4.76)	(4.75)
$\ln(GDP(t\text{-}1)_G)$-$\ln(GDP(t\text{-}1)_H)$	8.96	4.79	5.64	4.67	4.55
	(7.61)	(5.40)	(7.50)	(5.41)	(5.44)
$\ln(GDP(t\text{-}2)_G)$-$\ln(GDP(t\text{-}2)_H)$	-1.58	-10.07***	-4.93	-9.84**	-9.94**
	(4.47)	(3.86)	(4.44)	(3.86)	(3.86)
Married	-5.19***	1.98	-5.07***	2.49	2.32
	(1.12)	(4.62)	(1.13)	(4.48)	(4.49)
Married living separated	-5.74***	-1.67	-5.18***	-1.23	-1.29
	(1.66)	(4.71)	(1.65)	(4.59)	(4.63)
Divorced	-2.75**	0.22	-3.04**	0.71	0.67
	(1.38)	(4.43)	(1.38)	(4.28)	(4.31)
Widowed	-6.91***	-1.35	-6.57***	-0.89	-0.84
	(1.44)	(4.39)	(1.45)	(4.26)	(4.29)
Employed	-1.87***	-1.44**	-2.38***	-1.42**	-0.95
	(0.44)	(0.61)	(0.44)	(0.60)	(0.62)
Family at Home	3.42***	16.96	2.78***	16.03	15.72
	(0.49)	(12.91)	(0.51)	(12.32)	(12.39)
Spouse at Home	-2.45		-2.02		
	(1.94)		(1.92)		
Attended School in Germany	-0.14	-26.46***	0.83	-26.33***	-26.84***
	(1.14)	(1.30)	(1.14)	(1.28)	(1.32)
Children?	3.85***	-0.48	3.46***	-1.33	-1.52
	(0.52)	(3.81)	(0.52)	(3.65)	(3.63)
Aged 60 or older	4.08***	3.44***	4.45***	3.49***	3.32***
	(0.70)	(0.92)	(0.71)	(0.92)	(0.93)
Time in Germany	0.60***	-0.73	0.40*	-0.74	-0.73
	(0.21)	(0.51)	(0.21)	(0.49)	(0.49)
Time in Germany^2	-0.05***	0.04**	-0.04***	0.05**	0.04**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Time in Germany^3	0.00***	-0.00*	0.00***	-0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Disadvantage due to origin?	-1.92***	-1.52***	-1.73***	-1.46***	-1.42***
	(0.39)	(0.51)	(0.39)	(0.51)	(0.51)
Writing German?	-1.23*	0.20	-1.36**	0.28	0.32
	(0.65)	(1.12)	(0.65)	(1.09)	(1.08)
Speaking German?	-1.36	-0.70	-2.05	-0.55	-0.48
	(1.78)	(3.66)	(1.76)	(3.69)	(3.70)
Language Newspaper German?	7.80***	2.08**	6.11***	2.07**	2.03**
	(0.50)	(0.91)	(0.55)	(0.91)	(0.92)
Income					-0.00**
					(0.00)
Happiness					0.18
					(0.12)
Constant	-60.06***	38.12	-41.82**	39.46	39.41
	(17.72)	(50.03)	(18.04)	(50.47)	(50.19)
Country Region	No	No	Yes	No	No
Bundesland FE	No	No	Yes	Yes	Yes
R^2	0.14	0.67	0.17	0.67	0.67
Number of Clusters		1083		1083	1083
Observations	7129	7129	7098	7098	7098

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the predicted realization. The columns that include the number of clusters, include individual fixed effects and those standard errors are clustered. Furthermore we have done random sampling to get half of the sample to deduce the coefficients and then imputed for the other half the predicted realization.

Table 2.12: Difference between the Intentions and the Return, Behavioral Factors

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(GDP_G)-\ln(GDP_H)$	-5.04	-6.94	-6.78**	9.50***	4.67	4.17
	(3.68)	(4.57)	(2.91)	(3.12)	(12.25)	(12.25)
$\ln(GDP(t\text{-}1)_G)-\ln(GDP(t\text{-}1)_H)$	13.94***	17.71***	20.25***	17.92***	-1.68	-1.45
	(4.54)	(6.17)	(3.75)	(5.13)	(10.94)	(10.92)
$\ln(GDP(t\text{-}2)_G)-\ln(GDP(t\text{-}2)_H)$	-6.51*	-7.82*	-15.94***	-27.59***	0.91	1.42
	(3.45)	(4.38)	(3.22)	(3.27)	(7.04)	(7.03)
Married	-1.36	-1.52	0.31	4.75***	-5.21*	-5.28*
	(2.33)	(2.92)	(0.75)	(0.40)	(2.68)	(2.76)
Married living separated	-0.77	-0.81			-4.13	-4.16
	(2.72)	(3.67)			(2.95)	(3.03)
Divorced	-2.57	-2.90	1.20	7.27***	-7.95***	-7.83***
	(2.44)	(3.01)	(2.66)	(1.27)	(2.83)	(2.90)
Widowed	-2.12	-2.24			-6.19**	-6.22**
	(2.49)	(3.00)			(2.99)	(3.04)
Employed	-0.88*	-0.39	-1.53**	-3.00***	-3.45***	-3.47***
	(0.51)	(0.56)	(0.68)	(0.52)	(0.98)	(0.99)
Family at Home	6.00	4.72			11.02***	11.25***
	(5.83)	(6.01)			(0.95)	(0.94)
Attended School in Germany	-25.35***	-25.01***				
	(1.09)	(1.19)				
Time in Germany	-0.63*	-0.69*	0.99**	-0.33	-0.39	-0.38
	(0.36)	(0.41)	(0.46)	(0.23)	(0.73)	(0.72)
Children?	-3.54	-2.94	-11.06***	-1.40***		
	(2.40)	(2.35)	(4.08)	(0.43)		
Aged 60 or older	3.48***	3.75***	3.26***	5.16***	3.71***	3.71***
	(0.73)	(0.80)	(0.71)	(0.59)	(1.24)	(1.25)
Income	-0.00	-0.00	0.00	0.00***	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Happiness	0.21**	0.23**	0.52***	0.37***	0.01	0.00
	(0.09)	(0.11)	(0.10)	(0.08)	(0.13)	(0.13)
Disadvantage due to origin?	-0.75**	-0.72*			-1.22**	-1.23**
	(0.37)	(0.43)			(0.59)	(0.59)
Writing German?	0.63	0.71			1.18	1.19
	(0.86)	(0.92)			(1.86)	(1.86)
Speaking German?	-0.62	-0.44			-4.12*	-4.12*
	(2.60)	(3.28)			(2.48)	(2.49)
Language Newspaper German?	0.93	0.96			1.84	1.83
	(0.69)	(0.77)			(1.24)	(1.25)
Control Over Life		1.07*				
		(0.58)				
Remitting			-2.40***			
			(0.61)			
Ever paid remittances?				-5.03***		
				(0.38)		
Medium low risktaker					-0.44	
					(0.59)	
Medium high risktaker					0.11	
					(0.72)	
High risktaker					-1.00	
					(1.14)	
Risktaker?						0.09
						(0.56)
Constant	-11.14	-13.31	-35.27***	-41.35***	-3.59	-4.14
	(7.93)	(10.72)	(10.19)	(2.27)	(17.27)	(16.97)
Bundesland FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.68	0.67	0.54	0.15	0.78	0.78
Number of Clusters	1950	1747	1749		1278	1278
Observations	12336	10572	17967	17976	4898	4898

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the predicted realization. The columns that include the number of clusters, include individual fixed effects and those standard errors are clustered.

time horizon that they have left to live, shortens every year that they have spent in Germany and therefore their prediction gets better and more accurate. This goes along the findings of Smith et al. (2001), who using the Health and Retirement Survey (HRS), find that longevity expectations are consistently linked to subsequent observed mortality. The participants of the HRS have reached a retirement age, and therefore their evidence coincides with ours.[25] Another interpretation of the results leads towards Kahneman (2011) description of "what you see is all there is" (WYSIATI). As shortly mentioned when we presented the results of people's intentions, there seems to be bunching at 5, 10, 15 years, which points toward a simplifying heuristic at work. WYSIATI goes into the same direction. When you ask people about returning to their home country, things they like about their culture or home country become more salient. This in turn may also make their wish to return more salient and thereby bias the given answer.

In the introduction we mention that the findings would be relevant for government action. As it is not clear what really drives these differences, we need to be careful when giving policy advice. Future research needs to ask the question, where policy interventions would help, and whether the intentions that people provide really coincide with their future actions taken. As an example, if an individual thinks that she will return in less than five years, she may not start to integrate properly. As it turns out, this individual will stay longer than she thought at first. The time that the individual spent thinking that she may return quicker could therefore have been used more efficiently, as an example for Germany, the individual could have started to learn German.

To conclude, this chapter presented relevant information about the fact that migrants underestimate their stay in the country of origin, but there also seems to be a learning effect. The longer they are in the host country, the older they become and the better their forecasts become.

[25] Another example that uses the HRS is Sergeant et al. (2010) who analyzed retirement migration and found that individuals predicted moves into a community correctly, but did not predict the move into nursing facilities.

2.A Data Addendum

2.A.1 Possible Differences between Dustmann's Approach and our Approach

The "bioimmig.dta" file that is supplied by the SOEP (in a panel form) is used. In this data set the variable called "bistay" informs us about the individual's intentions and the variable "bistayy" tells us how long they plan to stay in Germany. This structure seemed appealing, since - only the different information on the address log needed to be merged to the existing panel structure. It was necessary to pay attention to the fact that the information on the address log about the return is at the household and not at the the individual level. Throughout the process of merging we came across 3 people that split off their current household - their household moved out of Germany, while they stayed in Germany.

One possible difference between our approach and Dustmann (2003a)'s approach could be that he constructed the panel himself, even though the information on the "bistay" variable should be the same, whether we use the "bioimmig.dta" or whether we use the personal files for each year and append them.

Table 2.13: Return Frequency 1985 - 1997

Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	Total
Return	163	67	59	74	53	41	29	35	36	43	35	31	22	688
Pct	4.74	1.95	1.72	2.15	1.54	1.19	0.84	1.02	1.05	1.25	1.02	0.90	0.64	20.02

Notes:Dustmann (2003a) Table 1

Table 2.14: Intentions and Realization 1984 - 1997

	Return between 84 and 97		
Intended Return (84)	No	Yes	Total
No	705	59	764
Percentage	29.73	14.29	27.44
Yes	1666	354	2020
Percentage	**70.27**	85.71	72.56
Total	2371	413	2784

Notes: Reproducing Dustmann (2003a) with my sample
Source: SOEP, own calculations.

Table 2.15: Intentions and Realizations 1984 - 1997 Dustmann (2003a) Table 2

	Return between 84 and 97		
Intended Return (84)	No	Yes	Total
No	665	98	763
Percentage	30.37	15.91	27.19
Yes	1525	518	2043
Percentage	69.63	84.09	72.81
Total	2190	616	2806

Notes: Dustmann (2003a) Table 2

2.A.2 Intentions and Residence Status

Different than in Table 2.2, the amounts off the diagonal are not as big anymore; out of those present in 1996 and saying that they want to return, only 38% never return. The time horizon has become significantly smaller and between 60 to 70% of the respondents seem to predict their return correctly. Nevertheless the nearly 40% of the population that do not predict their future correctly do not present simple noise. Again individuals seem to tell the truth about their intentions as it does not depend on their residence status. Out of those that have a limited residence status, 65% claim that they want to stay in Germany forever.

Table 2.16: Intentions and Realization 1996 - 2009

	Return between 96 and 09		
Intended Return (96)	No	Yes	Total
No	870	35	905
Percentage	60.80	30.97	58.61
Yes	561	78	639
Percentage	39.20	69.03	41.39
Total	1431	113	1544

Source: SOEP, own calculations.

Table 2.17: Desire to Return versus Residence Status 1996

	Residence Status		
Desire to Return	Unlimited	Limited	Total
Within 12 Months	0	2	2
(Percentage)	0.00	2.38	1.40
After One Year	24	27	51
Percentage	40.68	32.14	35.66
Stay in Germany Forever	35	55	90
Percentage	59.32	65.48	62.94
Total	59	84	143

Source: SOEP, own calculations.

Table 2.18: Socioeconomic Differences for Stayers

	Right Censored Obs			**Attritors**			
Variable	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**t-stat**
Male	0.54	0.50	1209	0.48	0.50	2682	(-3.52)***
Age at Migration	30.42	11.14	1209	29.87	10.43	2682	(-1.49)
$\ln(\text{GDP}_\text{G})$-$\ln(\text{GDP}_\text{H})$	1.68	1.25	1192	1.69	1.02	2646	(0.29)
Married	0.80	0.40	1209	0.57	0.50	2355	(-14.38)***
Married living separated	0.02	0.15	1209	0.02	0.14	2355	(-0.53)
Divorced	0.07	0.26	1209	0.04	0.20	2355	(-4.10)***
Widowed	0.06	0.25	1209	0.05	0.21	2355	(-2.25)
Employed	0.50	0.50	1209	0.54	0.50	2681	(2.39)*
Family at Home	0.31	0.46	1203	0.14	0.35	2673	(-12.05)***
Spouse at Home	0.01	0.09	1209	0.02	0.15	2682	(3.15)***
Attended School in Germany	0.04	0.20	1189	0.03	0.16	2643	(-2.56)*

Source: SOEP, own calculations.
Note: The t-statistics test for the significance of the difference between right censored individuals and those that disappear before 2008. For each individual the last point in time where information is provided in the data set is taken to get the different means.

Table 2.19: Country of Origin

Country	Frequency	Percent
Turkey	9,670.0	22.9
Ex-Yugoslavia	4,357.0	10.3
Greece	3,824.0	9.1
Italy	4,996.0	11.9
Spain	2,326.0	5.5
Austria	518.0	1.2
France	304.0	0.7
Benelux	75.0	0.2
Great Britain	251.0	0.6
USA	186.0	0.4
Switzerland	127.0	0.3
Romania	1,170.0	2.8
Poland	2,650.0	6.3
Iran	139.0	0.3
Hungary	224.0	0.5
Portugal	80.0	0.2
Bulgaria	114.0	0.3
Czech Republic	287.0	0.7
Russia	2,012.0	4.8
Philippines	156.0	0.4
Kazakhstan	1,561.0	3.7
Albania	80.0	0.2
Kirgistan	88.0	0.2
Ukraine	415.0	1.0
Tadzhikistan	67.0	0.2
Vietnam	67.0	0.2
Netherlands	236.0	0.6
Croatia	1,439.0	3.4
Bosnia Herzegovina	848.0	2.0
Macedonia	164.0	0.4
Slovenia	192.0	0.5
Kosovo Albania	163.0	0.4
Eastern Europe	1,578.0	3.7

Source: SOEP, own calculations.

Table 2.20: Difference between the Intentions and the 'rational' Expectations 1984 - 1996

	85	86	87	88	89	90	91	92	93	94	95	96
Male	-1.16	-3.82**	-3.14**	-3.27**	-1.43	-0.19	-2.62	-0.79	0.49	-2.42	-2.78*	-1.01
	(1.48)	(1.48)	(1.48)	(1.50)	(1.59)	(1.61)	(1.60)	(1.63)	(1.65)	(1.65)	(1.67)	(1.29)
Age at Migration	0.31***	0.40***	0.39***	0.19*	0.27***	0.08	-0.05	0.06	0.21	0.17	0.06	0.33***
	(0.09)	(0.09)	(0.09)	(0.10)	(0.11)	(0.11)	(0.12)	(0.13)	(0.13)	(0.14)	(0.15)	(0.08)
$\ln(GDP_G)$-$\ln(GDP_H)$	-4.04***	-4.04***	-3.80***	-2.16**	-2.34**	-2.97***	-1.01	-3.98***	-2.41**	-0.63	-3.59***	2.40***
	(0.94)	(0.92)	(0.90)	(0.93)	(0.96)	(0.97)	(0.96)	(0.99)	(1.01)	(1.01)	(1.03)	(0.71)
Employed	-9.21***	-7.19***	-8.47***	-6.38***	-5.22**	-8.85***	-3.96	-3.20	-4.60*	-1.83	1.51	-4.55**
	(2.11)	(2.25)	(2.26)	(2.15)	(2.53)	(2.61)	(2.60)	(2.65)	(2.56)	(2.77)	(2.80)	(2.04)
Spouse at Home	2.77	6.12**	6.26**	3.54	6.93**	6.50*	6.50*	2.25	-2.43	-2.73	2.16	-5.05
	(3.08)	(3.03)	(2.92)	(3.34)	(3.14)	(3.59)	(3.73)	(4.10)	(4.02)	(4.44)	(4.63)	(5.15)
Attended School in Germany	2.26	3.18	3.28	7.35**	2.90	-2.63	-3.38	2.30	4.09	5.08	9.22**	1.92
	(3.57)	(3.40)	(3.32)	(3.71)	(3.58)	(3.78)	(3.67)	(3.81)	(3.75)	(4.00)	(4.14)	(3.78)
Time in Germany	-4.54***	-3.84***	-4.70***	-5.26***	-1.06	-1.59	-4.43*	-3.99	-2.85	-6.48**	-1.84	-0.72
	(1.34)	(1.30)	(1.47)	(1.71)	(1.95)	(2.24)	(2.40)	(2.70)	(2.92)	(3.00)	(3.74)	(0.80)
Time in Germany^2	0.33***	0.26***	0.29***	0.29***	0.07	0.10	0.24**	0.22*	0.15	0.29**	0.10	-0.01
	(0.09)	(0.09)	(0.09)	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.16)	(0.04)
Time in Germany^3	-0.01***	-0.00**	-0.00***	-0.00**	-0.00	-0.00	-0.00*	-0.00*	-0.00	-0.00**	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income	0.00	0.00	0.00**	0.00	0.00	0.00***	0.00	0.00	0.00	-0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Happiness	0.84***	0.89***	0.60**	0.66**	0.91***	0.20	0.69*	-0.37	0.42	-0.86**	0.17	-0.11
	(0.29)	(0.29)	(0.30)	(0.33)	(0.34)	(0.35)	(0.36)	(0.37)	(0.36)	(0.38)	(0.39)	(0.32)
Aged 60 or older	3.15	3.09	3.48	6.29**	5.78**	9.82***	10.83***	10.33***	7.30***	7.34***	9.25***	0.37
	(3.28)	(3.15)	(2.91)	(2.92)	(2.84)	(2.79)	(2.68)	(2.76)	(2.69)	(2.66)	(2.65)	(2.15)
Married		11.26	18.64**	10.87	8.87	16.32*	26.17***	20.64***	14.67**	18.19***	19.02***	-3.48
		(13.52)	(8.93)	(10.17)	(10.21)	(8.62)	(8.27)	(7.41)	(6.30)	(5.70)	(5.60)	(2.54)
Divorced							31.74	32.08	33.05	31.87	22.83	-0.35
							(20.54)	(20.95)	(20.75)	(20.41)	(19.93)	(3.94)
Widowed									-21.08			-3.04
									(21.85)			(4.13)
Married living separated												1.03
												(4.85)
Family at Home												2.06
												(2.33)
Constant	-22.71**	-43.19***	-31.93***	-10.24	-46.20***	-28.44*	-13.04	-5.59	-0.84	33.65	-8.23	-2.37
	(9.52)	(8.71)	(9.61)	(13.44)	(12.90)	(15.06)	(16.81)	(19.51)	(24.74)	(25.85)	(31.21)	(20.59)
Country Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bundesland FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15	0.18	0.15	0.16	0.17	0.11	0.15	0.13	0.15	0.15	0.16	0.23
F-stat.	9.13	9.77	7.39	7.12	7.85	5.06	6.14	4.79	5.16	5.17	4.95	8.37
p-val.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	1367	1254	1195	1115	1094	1050	988	938	896	827	755	1252

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the 'rational' expectation.

Table 2.21: Difference between the Intentions and the 'rational' Expectations 1997 - 2008

	97	98	99	00	01	02	03	04	05	06	07	08
Male	0.80	0.84	-0.37	0.23	-1.02	-0.67	-0.32	-0.72	0.04	0.29	0.09	-0.46
	(1.44)	(1.37)	(1.27)	(1.26)	(1.04)	(0.98)	(0.97)	(0.98)	(0.99)	(1.04)	(1.04)	(1.08)
Age at Migration	0.23**	0.18**	0.16*	0.25***	0.18***	0.19***	0.07	0.03	0.05	0.06	-0.01	0.12
	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
$\ln(GDP_G)$-$\ln(GDP_H)$	1.75**	1.91***	1.88***	2.13***	2.38***	2.05***	2.41***	1.80***	1.09**	1.91***	2.09***	2.85***
	(0.75)	(0.72)	(0.66)	(0.65)	(0.52)	(0.49)	(0.49)	(0.49)	(0.51)	(0.53)	(0.54)	(0.57)
Married	-11.31***	-8.87***	-4.57	-5.28*	0.46	0.82	4.27*	-4.67*	-0.19	-6.80**	-5.56*	-8.38***
	(3.23)	(3.23)	(3.07)	(3.10)	(2.23)	(2.22)	(2.44)	(2.49)	(2.68)	(2.81)	(2.97)	(3.19)
Married living separated	-14.20**	-4.83	-0.33	0.14	-5.65	-0.27	8.21**	-2.30	-2.16	-12.85***	-7.85*	-6.48
	(5.96)	(6.04)	(5.96)	(5.77)	(4.30)	(3.91)	(3.93)	(4.02)	(3.82)	(4.04)	(4.11)	(4.45)
Divorced	-5.34	-8.11*	-3.75	-6.12	1.60	0.34	6.99**	-2.21	1.59	-4.68	-3.82	-9.24**
	(4.55)	(4.39)	(4.00)	(3.95)	(2.94)	(2.93)	(3.05)	(3.00)	(3.25)	(3.32)	(3.42)	(3.63)
Widowed	-14.08***	-9.79*	-3.29	-4.19	1.07	-2.44	3.49	-4.66	0.99	-6.83*	-6.76*	-9.02**
	(5.08)	(5.00)	(4.37)	(4.60)	(3.51)	(3.36)	(3.47)	(3.44)	(3.45)	(3.67)	(3.70)	(3.82)
Employed	1.58	-0.81	11.53***	-2.14	-0.09	-2.31*	-4.96***	-3.46**	-3.52**	-6.24***	-3.74**	-3.95**
	(2.22)	(1.96)	(3.20)	(1.89)	(1.52)	(1.28)	(1.32)	(1.37)	(1.42)	(1.44)	(1.46)	(1.54)
Family at Home	2.86	4.13*	4.06**	3.11*	2.06	1.11	2.01*	1.04	2.21*	3.23***	0.43	1.48
	(2.34)	(2.11)	(1.82)	(1.80)	(1.26)	(1.18)	(1.14)	(1.15)	(1.16)	(1.22)	(1.20)	(1.24)
Spouse at Home	-0.42	0.13	-6.33	0.28	-0.61	-3.19	-4.39	-2.77	-2.05	2.09	6.63	3.17
	(5.59)	(5.97)	(5.19)	(5.40)	(5.33)	(5.01)	(5.54)	(5.21)	(5.40)	(5.41)	(5.64)	(5.51)
Attended School in Germany	-4.14	2.62	5.56*	-3.22	-0.92	2.45	2.27	0.23	0.97	-0.19	1.27	3.07
	(3.79)	(3.68)	(3.33)	(3.25)	(2.70)	(2.70)	(2.48)	(2.51)	(2.66)	(2.59)	(2.57)	(2.59)
Time in Germany	-2.07**	-0.33	-0.34	1.07	0.89*	-0.29	0.72	-0.22	-0.58	0.02	0.59	0.33
	(0.89)	(0.91)	(0.82)	(0.86)	(0.53)	(0.50)	(0.52)	(0.51)	(0.53)	(0.54)	(0.63)	(0.68)
Time in Germany^2	0.07	-0.01	-0.01	-0.07*	-0.05**	0.01	-0.04	0.00	0.01	-0.01	-0.03	-0.02
	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Time in Germany^3	-0.00	0.00	0.00	0.00**	0.00**	0.00	0.00*	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Income	0.00	0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Happiness	0.02	-0.20	-0.15	0.12	-0.05	-0.26	0.11	-0.06	0.58**	0.50*	0.32	0.36
	(0.37)	(0.35)	(0.32)	(0.33)	(0.29)	(0.28)	(0.26)	(0.26)	(0.25)	(0.27)	(0.28)	(0.28)
Aged 60 or older	3.72	2.87	1.87	1.04	1.54	0.92	2.29	4.75***	3.34*	2.86	4.45**	2.44
	(2.38)	(2.31)	(2.06)	(2.06)	(1.80)	(1.77)	(1.75)	(1.79)	(1.78)	(1.87)	(1.89)	(1.94)
Disadvantage due to origin?	-4.18***	-1.43	-4.44***	-2.33**	0.34	-1.02	-1.84*	-1.87*	-0.31	1.16	-1.00	0.05
	(1.29)	(1.25)	(1.15)	(1.18)	(1.00)	(0.98)	(0.96)	(0.98)	(1.01)	(1.02)	(1.02)	(1.10)
Writing German?	-0.31	-3.12*	1.58	1.26	-1.27	-1.59		13.32*	0.63	-2.13	-4.52**	-5.75***
	(1.85)	(1.82)	(1.68)	(1.68)	(1.54)	(1.52)		(6.99)	(1.72)	(1.78)	(1.81)	(1.94)
Speaking German?	5.89	1.01	7.36	-1.30	0.11	4.25	4.69	3.72	0.87	-2.35	-2.50	-0.60
	(6.57)	(5.41)	(5.80)	(5.31)	(4.45)	(3.79)	(3.60)	(3.51)	(4.13)	(4.62)	(5.23)	(5.12)
Language Newspaper German?	6.42***	8.78***	6.48***	5.27***	5.35***	9.10***	3.77***	4.29***	3.64**	4.60***	2.47*	7.62***
	(1.60)	(1.55)	(1.50)	(1.56)	(1.33)	(1.32)	(1.30)	(1.33)	(1.42)	(1.42)	(1.45)	(1.56)
Constant	-19.92*	0.60	-29.83*	-24.87*	-17.52*	-15.58*	-27.94***	-21.98*	-15.92	-16.60	-7.30	-12.28
	(11.57)	(14.99)	(15.30)	(15.04)	(9.32)	(8.31)	(10.60)	(11.99)	(10.10)	(13.10)	(17.01)	(16.62)
Country Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bundesland FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.28	0.25	0.27	0.22	0.19	0.20	0.17	0.16	0.17	0.19	0.16	0.20
F-stat.	7.38	6.38	6.80	5.31	5.72	5.88	4.61	4.23	4.22	4.49	3.36	3.88
p-val.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	920	960	937	938	1265	1194	1186	1171	1075	979	907	805

Source: SOEP, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. The dependent variable is the difference between the intended return and the 'rational' expectation.

Chapter 3

Bereavement Effects and Early Life Circumstances[1]

3.1 Introduction

Bereavement of a close family member is a stressful and traumatic event that occurs mostly later in life.[2] Papers such as Lindeboom et al. (2002) and van den Berg et al. (2012) have shown the detrimental impact of bereavement and grief on economically relevant outcomes, such as health, the familial situation, and labor market outcomes. In particular, van den Berg et al. (2012) find that grief can cause persistent effects on labor market participation. Therefore, a deep investigation of bereavement effects, resilience and the influencing factors of coping is important for the society and for the economy.

Latest since Barker (2007), economists are interested in early life circumstances and what long run effects are caused by detrimental conditions in utero or childhood. Almond and Currie (2011) give a concise overview of such long run effects.[3] The Second World War (WW2) created a very specific and stressful environment.[4] It is quite likely that those individuals who grew up without their father or were exposed to bombardments or combat actions, as an example, had a stressful time. As an example, around 70 cities were destroyed due to the war (about 333

[1]This chapter is co-authored with Gerard J. van den Berg and Anna Hammerschmid.

[2]Examples of articles focusing on bereavement are Siflinger (2013), van den Berg et al. (2012), van den Berg et al. (2011a), van den Berg and Drepper (2011), Espinosa and Evans (2008) and for a thorough literature overview see Hansson and Stroebe (2007).

[3]Other examples in this line of literature are: Doblhammer et al. (2011), van den Berg and Lindeboom (2013), Tough (2013), Elder (1999).

[4]In the context of the WW2, we refer the reader to a current literature strand in economics, which deals with early life circumstances and the WW2, see e.g., van den Berg et al. (2011b), Jürges (2012), Akbulut-Yuksel (2009), Akbulut-Yuksel et al. (2013), Kesternich et al. (2013), Kesternich et al. (forthcoming).

km^2 with 2,164,800 housing losses and thus around 7,500,000 persons were made homeless in Germany (Hewitt, 1983)). According to Radebold (2009) about a quarter of German children grew up without a father. This number is not surprising if we take a look at the casualties the war caused; Radebold (2009) reports cohort death rates of 45% for those between the ages of 20-25 years, 56% for the 25-30 year olds, 36% for the 30-35 year olds, and 29% for the 35-40 year olds. The question may thus be raised how these individuals cope with stressful events later in their life. Are they less resilient to the stress caused by bereavement following traumatic experiences, or does it evoke emotions from their early remembrances?

The psychology literature suggests phenomena such as *posttraumatic stress disorder (PTSD)* following traumatic experiences (for a review of research on long-run effects associated with WW2 trauma in elderly Germans see e.g., Glaesmer, 2013), and *trauma re-activation* or *re-traumatization* (see e.g., Macleod, 1994; Kaup et al., 1994; Heuft, 2004). This suggests that those individuals exposed to stressful events early in life suffer from stress later in life due to trauma reactivation. Furthermore the psychologists define *late-onset stress symptomatology (LOSS)*, which in our context can be related to bereavement later in life (see e.g., Davison et al., 2006).[5]

In this chapter, we are interested in the role of early life circumstances in combination with bereavement effects late in life. Specifically, we analyze father's absence or exposure to air raids or combat actions in the context of WW2 in Germany in combination with the effects of late life bereavement. In order to prepare the individuals accordingly for the eventual *PTSD* or *LOSS*, it is important to study whether individuals have difficulties to cope with grief later in life if they were exposed to air raids, combat actions or father's absence. Analyzing whether exposure causes depression or other health related consequences, which in turn may affect financial wealth or care taking abilities, is important for the society as they will bear the cost of something preventable.

The underlying question of the growing literature is whether shocks early in life mediate or worsen the impact of negative events later in life (see e.g., van den Berg and Schoch (2013),

[5]Furthermore the psychology literature analyzes cumulative trauma exposure, for more details in this research area see e.g., Ogle et al. (2014) who give an overview and references therein. Ogle et al. (2014) find a strong association between cumulative exposure and *PTSD* symptom severity. Furthermore they pin down the event categories that show the strongest relationship to symptom severity; beginning with the strongest association: "cumulative exposure to childhood violence, adult physical assaults, war zone exposure, sexual assaults, death/illness" (see Ogle et al., 2014). However, they emphasize that a causal interpretation of their analysis might be problematic.

Hayward et al. (2013), and van den Berg et al. (2010)).[6]

We contribute to this literature by estimating a joint treatment effect of adverse early life circumstances (father's absence or exposure to air raid or combat actions in the context of WW2 in Germany) and a late life event (bereavement of a close family member) on (mental) health, life and sleep satisfaction. Besides this measure of the general mental state we include life and sleep satisfaction because they may be better at capturing the actual stress level. A recent study by Rosekind et al. (2010) shows that sleep problems, such as insomnia or insufficient sleep syndrome, are negatively related to workplace productivity measures as well as safety. To measure the combined effect of detrimental early-life circumstances and bereavement, we use a first difference approach, thereby accounting for all time-invariant confounding factors. The first difference approach is outlined in Section 3.2 and follows the literature (see e.g., Lindeboom et al. (2002), van den Berg et al. (2010), van den Berg and Schoch (2013)).

One of the contributions of this article is the novel data - the "Frühe Kindheitsmodul" (FKM). A survey on childhood circumstances in the context of the WW2 and the postwar period in Germany. It can be linked to the German Socio Economic Panel (SOEP) and we are the first to do so. This allows us to link stressful events during WW2 to a rich set of information on bereavement, health, life and sleep satisfaction. Moreover, to the best of our knowledge, we are the first to analyze the specific causal interaction effect with bereavement in the context of the WW2. The interplay between an absent father, air raid or combat action exposure in combination with bereavement later in life gives us a novel insight into grief and bereavement effects.

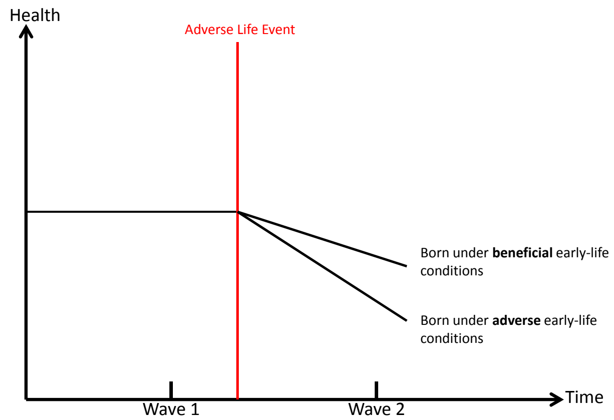
Figure 3.1 depicts our expectations that an individual hit by an adverse life event is affected less in terms of mental health if she has been exposed to beneficial early-life conditions (e.g., not exposed to air raids or battlefield).[7] One of the major differences of this chapter to van den Berg et al. (2010) is that our individuals are exposed to detrimental early-life conditions during

[6] van den Berg et al. (2010) analyze the interplay between the business cycle at birth and the effect of adverse events late in life on cognition using the Dutch LASA. They find that the effect of stroke, surgery, and illness/death of a family member is worse for those who were born during a recession. Moreover, they find evidence for a differential impact on men and women. van den Berg and Schoch (2013) use the SHARE data to examine the influence of economic conditions at birth on the mental health effect (cognition, depression) of adverse events later in life. Hayward et al. (2013) test the "Predictive Adaptive Response (PAR) hypothesis" for mortality and fertility, which states that poor nutrition early in life leads to adaption, making the individual more resistant to poor nutrition later in life. Their findings are not in line with the PAR hypothesis. Moreover, they find heterogeneous effects with respect to socio-economic status and age.

[7] Figure 3.1 is similar to van den Berg et al. (2010) (Figure 1).

childhood.[8]

Figure 3.1: Potential Role of Early Life Conditions on the Effect of Adverse Events Later in Life on Mental Health



As expected, we find a significant negative interaction effect of father's absence, exposure to air raids or combat actions and bereavement on mental health. Similarly, we find a negative interaction effect of bereavement and father's absence on life and sleep satisfaction. The satisfaction results point into the direction that the individuals suffer from stress. For exposure to air raids or combat actions and bereavement of a close family member, we find a negative effect on the satisfaction outcomes, which is only significant in the case of life satisfaction. Our findings underline the importance of the early life environment to develop the ability to cope with grief later in life.

These results are robust to certain sensitivity checks, such as excluding cancer deaths, and those observations where life and sleep satisfaction cannot have an increase or a decrease.[9] In line with the literature we also perform an effect heterogeneity test with respect to gender (see e.g., van den Berg et al., 2010) and socioeconomic status (see e.g., Hayward et al., 2013).

[8]The period during childhood varies depending on which early-life circumstance we focus on. For father's absence, it is possible that the father was absent just before an individual reached the age of 13 years, but it could have been that the father was absent when the individual was only a couple of months old. For the air raid or battlefield exposure, the individual can at most be 9 years old.

[9]This means that satisfaction value was at its peak in one year (cannot increase) or at its low (cannot decrease).

The remainder of this chapter is structured as follows, Section 3.2 explains the empirical strategy, and discusses its possible shortcomings. Section 3.3 presents the data and provides an overview of the key variables used. Section 3.4 describes the results and Section 3.5 concludes.

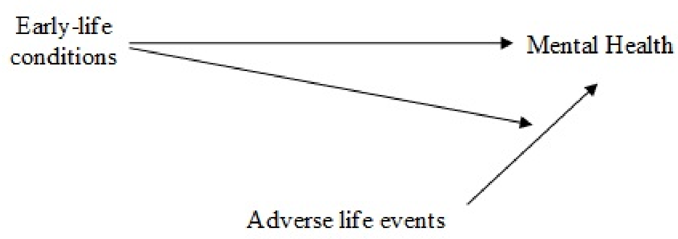
3.2 Empirical Strategy

Similar as in van den Berg et al. (2010) (see Figure 3.2, very close to Figure 2 in van den Berg et al. (2010)) our analysis focuses on the interplay between early-life conditions (father absence or exposure to air raids or battlefield) and adverse life events (death of close family member) with mental health or life/sleep satisfaction later in life. Our empirical specification follows for example Lindeboom et al. (2002), van den Berg et al. (2010), and van den Berg and Schoch (2013). We consider a similar relationship between mental health H_{it} (or life/sleep satisfaction) and a range of socio-economic variables X_{it}, a life event variable D_{it}, an early-life circumstance indicator E_{it}, an interaction between the life event and the early-life circumstance $D_{it} * E_i$, time-invariant individual characteristics α_i, and an idiosyncratic shock u_{it}.

$$H_{it} = X_{it}^{'}\beta + D_{it}\gamma + E_i\theta + D_{it}E_i\delta + \alpha_i + u_{it} \tag{3.1}$$

In this context, H_{it}, X_{it}, D_{it} and E_i are observed, while α_i and u_{it} are unobserved. γ and δ are the parameters of interest since γ captures the effect of the life event on mental health, and δ captures the interaction effect of the early life circumstances and the life event on mental health. If we wanted to estimate the effect of the life event on mental health via regular OLS, we would have to assume that X_{it}, D_{it} and $D_{it} * E_i$ are orthogonal to $\alpha_i + u_{it}$. As discussed in Lindeboom et al. (2002), it is usually assumed that this orthogonality condition holds. It may not be satisfied if there are unobservables in α_i or u_{it} that affect the outcome variable and any of the right hand side variables.

Figure 3.2: Early-Life Conditions, Adverse Life Events and Later-life Mental Health



To overcome the endogeneity problem due to time-invariant unobservables (α_i), we use the first difference approach. Again, we refer the reader to Lindeboom et al. (2002) for a discussion of the three possible empirical approaches to deal with this sort of endogeneity. Due to the fact that we have a longitudinal data set at our hands, we can use the first difference approach without any problem. Taking first differences of Equation (3.1) leads to:

$$\Delta H_{it} = (\Delta X_{it})' \beta + (\Delta D_{it})\gamma + (\Delta D_{it} E_i)\delta + \Delta u_{it} \tag{3.2}$$

Δ denotes the first difference operator, e.g., $\Delta H_{it} := H_{it} - H_{i,t-1}$. ΔD_{it} equals one when the life event happened, meaning that the individual lost someone close. This is an irreversible event, thus $D_{it} = 1$ corresponds to $\Delta D_{it} = 1$.[10]

The drawback that results from a first differenced approach, as iterated in Lindeboom et al. (2002), is that time-invariant explanatory variables drop out of the estimation. In our case, this is relevant for the level of the early life events (father absence and air raid or combat exposure) as they drop out and may be interesting effects by themselves. However, as we are mainly interested in bereavement effects, i.e., the effect (and interaction effect) of a time-variant variable, this is only a minor problem.

3.3 Data

Our empirical analysis, uses the German Socio Economic Panel (SOEP) and a novel supplementary module called "Frühe Kindheit im (Nach-)Kriegskontext" (FKM). The SOEP is a longitudinal survey of households and individuals in Germany.[11] The FKM is a survey on childhood circumstances in the context of the Second World War (WW2) and the postwar period in Germany. As it is a novel survey, we provide a more detailed description of the contents and sampling in the Appendix 3.A.1.

Our information on (mental) health and bereavement in late life as well as some of the covariates for our empirical model stem from the SOEP, while the information on outcomes and bereavement is based on the waves from 2010, 2011, and 2012. The information on early

[10] We refer the reader to the data section, where we explain how this difference changes if an individual loses e.g., his mother in one wave and his father in the next.

[11] For further information about the SOEP, we refer the reader to Wagner et al. (2007). We use the Socio-Economic Panel (SOEP), data for years 1984-2012,version 29,SOEP,2013,doi:10.5684/soep.v29.

life exposure to stress is taken from the FKM. A detailed description of the main variables used is provided in the following sections.

3.3.1 Outcome Variables

Our main outcome variables are current life satisfaction, sleep satisfaction and overall mental health, as measured by the Mental Component Summary Scale (MCS) (provided biennially in the SOEP). The SOEP's MCS score is a z-transformed measure of mental health (mean: 50, standard deviation: 10) that is based on an explorative factor analysis and follows closely the SF-12v2 concept (see Andersen et al., 2007).[12] For life and sleep satisfaction, the respondents are explicitly asked to rate their satisfaction on a 0-10 scale, where 10 indicates highest and 0 indicates lowest satisfaction.

3.3.2 Bereavement

In the SOEP individuals are annually asked to provide information on whether and in which month their mother, father, child, partner or other family members died.

The general bereavement indicator D_{it} takes the value 1 if the partner, the mother, the father, the child or any other household person, died between t and t-1.[13] As explained in the empirical specification, we estimate our main specification using a first difference approach. To get a time-consistent measure of ΔD_{it}, we make the following adjustments; ΔD_{it} is missing if someone died in the previous period (t-1) and nobody died in the current period (t) or if a death occurred in both periods. These change ensure that only cases with no deaths between two waves are in the control group and cases with bereavement in the second wave of a two-wave-interval are in the treatment group.[14]

Since the health module is conducted on a biennial basis, we have information on the mental health score (MCS) for 2010 and 2012. We can thus only base our estimation on the first difference

[12] Following Ware et al. (2002) closely, Andersen et al. (2007) use eight subscales for the calculation of the MCS and Physical Component Summary Scale (PCS): "Physical Functioning, Role Physical, Bodily Pain, General Health, Vitality, Social Functioning, Role Emotional, and Mental Health". See Andersen et al. (2007) for a detailed description of the procedure, and the differences as well as the similarities to the original SF-12v2 (see e.g., Ware et al., 2002).

[13] Missing values of the sub indicators (for deaths of partner, mother, father, child, or other household members) are treated as 0, unless all the sub indicators are missing. In this case, also the general death indicator takes a missing value. A detailed description of the steps and adjustments used to generate the treatment variables is provided in Appendix 3.A.2.

[14] However, we want to emphasize that we do not tackle the initial conditions problem at this stage. We do not consider any information (on potential deaths) from the past when constructing the bereavement indicators for the intervals 2010-2011 and 2011-2012, respectively.

between 2012 and 2010. We have to make a further adjustment when generating ΔD_{it} for the analysis of MCS, making sure that ΔD_{health} captures deaths between 2010 and 2012.[15] For a detailed analysis regarding the actual timing of death within this two year interval, we generate two sub-indicators if bereavement occurred between the 2010 and 2011 waves or between the 2011 and 2012 waves. These two sub-indicators sum to ΔD_{health}.

The following section provides a detailed description of the early life variables (exposure to air raids, combat actions, and father's absence).

3.3.3 Early Life Circumstances

In the FKM, the individuals are asked whether they did not live in the same household as their father for more than 6 months up until the age of 13. This question is used as our indicator for father's absence.[16] Additionally, we have information on the duration and type of absence (war/prison).

We use the individual answers to four questions to generate an indicator of battlefield and air raid exposure. The first question refers to the respondents born between 1935 and 1944 and asks whether they remember air raids (Q1).[17] Moreover, those born between 1939 and March 1945 were explicitly asked whether they have experienced air raids in their first year of life (Q2).[18] We also include the information on whether the mother experienced air raids during pregnancy (cohorts 1940-45, Q3).[19] The final question we include asks about other combat actions in the immediate environment and refers to the cohorts 1935 until 1944 (Q4).[20]

The summary indicator of air raid/battlefield exposure is an aggregate measure of these four questions.[21] As covariates and for sensitivity analyses, we define age in months using the birth

[15]For a more detailed description of this adjustment, we refer the reader to the Appendix 3.A.2.

[16]Question: "Up until the age of 13, have you not lived with your father in the same household for at least 6 months?". This question and all of the following questions from the FKM questionnaire have been translated by the authors.

[17]Question Q1: "Do you remember air raids?".

[18]Question Q2: "Have you experienced air raids in your first year of life?".

[19]Question Q3: "Has your mother experienced air raids during pregnancy?".

[20]Question Q4: "Beside air raids, were there other combat actions in your direct environment that you could hear or see?". For every individual born outside the respective time frame, we infer the answer "no" because they cannot be affected. In addition, the categories "do not know" and "no" are treated as a denial in Q2 and Q3.

[21]It is 1 if any of the 4 variables takes the value 1. In a similar way, it is set to missing if any of the 4 variables is missing and 0 otherwise.

and interview months. Father's education is generated as an indicator for high socio-economic status (SES).[22]

3.3.4 Descriptive Statistics

Tables 3.1 and 3.2 show descriptive statistics for the MCS and life/sleep satisfaction estimation samples, respectively.[23] Since the sample for the analysis of the two early life events (father's absence and air raid/battlefield exposure) differ slightly, we report the descriptive statistics also separately for the two samples. The statistics are however very similar between the two samples. Moreover, there are only minor differences in these statistics across the samples for our outcome variables MCS and life/sleep satisfaction. The average age is between 68 and 69 years and there are slightly less men in all our samples which is due to the longer life expectancy of women. Less than one quarter of our sample has/had a father with a high education degree.

Table 3.1: Summary Statistics MCS

	(FA)		(AB)	
	Mean	SD	Mean	SD
Age (in months)	827.47	55.30	827.82	54.75
Age^2 (in months)	6.9e+05	91506.82	6.9e+05	90612.16
MCS	52.18	9.33	52.10	9.37
Males	0.49	0.50	0.49	0.50
High Father Education	0.24	0.42	0.24	0.43
Δ Age (in months)	11.77	1.16	11.76	1.16
Δ Age^2 (in months)	19337.12	2277.32	19334.05	2277.95
Δ MCS	-0.76	8.87	-0.83	8.94

Source: SOEP, own calculations.
Notes: (FA) stands for fahter absence sample, and (AB) stands for air raid battlefield sample.

Tables 3.3 and 3.4 give an overview on the number of treatment cases for our analysis. To make sure that our cell sizes do not decrease too much when interacting bereavement with the indicators for adverse early life conditions, we also show the number of cases for which both events have happened (interaction term = 1). Again, the differences between our samples are only minor. The number of bereaved cases is larger than 50 in the first interval (2010-2011) and does not exceed 40 in the second interval (2011-2012). For the interaction between bereavement and early life events, we have at most 25 cases in the first interval and less than 20 cases in the

[22]We define high SES as Realschule, Fachhochschule, Abitur, and low SES as: Hauptschule, no degree, no school attended.

[23]For the first difference analysis of life and sleep satisfaction, we use up to two observations per person. For the calculation of means and standard deviations in Table 3.2, we only use the first observation for each individual.

Table 3.2: Summary Statistics Satisfaction

	(FA)		(AB)	
	Mean	SD	Mean	SD
Age (in months)	818.14	55.08	818.53	54.52
Age^2 (in months)	6.7e+05	90089.83	6.7e+05	89162.61
Life Satisfaction	7.19	1.62	7.18	1.63
Satisfaction Sleep	6.78	2.24	6.77	2.25
Males	0.48	0.50	0.48	0.50
High Father Education	0.23	0.42	0.23	0.42
Δ Age (in months)	11.61	1.64	11.62	1.66
Δ Age^2 (in months)	18859.74	2916.55	18873.96	2938.83
Δ Life Satisfaction	-0.15	1.43	-0.16	1.43
Δ Satisfaction Sleep	0.00	1.91	0.01	1.92

Source: SOEP, own calculations.
Notes: (FA) stands for father absence sample, and (AB) stands for air raid battlefield sample.

second one.

Moreover, we provide histograms of life satisfaction, sleep satisfaction, and MCS (in levels and in first differences) in the Appendix 3.A.3. All outcome variables have a slightly left-skewed distribution in levels. However, the distributions of the first differenced outcome variables are fairly symmetric.

Table 3.3: Treatment Cases MCS

	ΔD 2010-2011		ΔD 2011-2012		ΔD_{health}	
	(FA)	(AB)	(FA)	(AB)	(FA)	(AB)
Adverse Life Event	53	56	34	34	87	90
Adverse Life Event * Early Life	22	23	16	16	38	39

Source: SOEP, own calculations.
Notes: (FA) stands for father absence sample, and (AB) stands for air raid battlefield sample.

Table 3.4: Treatment Cases Satisfaction

	ΔD 2010-2011		ΔD 2011-2012		ΔD_{total}	
	(FA)	(AB)	(FA)	(AB)	(FA)	(AB)
Adverse Life Event	58	61	39	40	97	101
Adverse Life Event * Early Life	25	24	19	17	44	41

Source: SOEP, own calculations.
Notes: (FA) stands for father absence sample, and (AB) stands for air raid battlefield sample.

Figure 3.3 plots different measures for the life and sleep satisfaction of the SOEP respondents over time. Panel (3.2a) plots the average life satisfaction over the whole SOEP horizon, and we can see that it is relatively stable around 7. The same holds for satisfaction sleep as Panel (3.2b) shows, it is more or less constant around 6.8. The time horizon is shorter for satisfaction sleep, as it has only been surveyed since 2008. Splitting our sample into war versus non-war cohorts, where the war cohorts are defined as being born between 1939 and 1945 we observe that the war cohorts are a little bit less satisfied with life and sleep (see Panels (3.2c) and (3.2d) and be aware of the scales). Panels (3.2e) and (3.2f) plot the relative number of individuals in the different cells, it emphasizes that 60 to 70% of the individuals in the SOEP have a life or sleep satisfaction between 7 and 10, while 20 to 30% have a life or sleep satisfaction between 3 and 7, and only about 10% are very unsatisfied with their life and sleep.[24] Splitting our sample by exposure to air raids or battlefield, or to father's absence or even both (panels (3.2g) and (3.2h)) we observe no clear difference in life or sleep satisfaction.[25]

3.4 Results

In this section, we describe the results of our empirical analyses. For our three outcome variables, we run a (pooled) OLS regression (Equation 3.1), and a first difference analysis (Equation 3.2). For the following results, we first regress the respective outcome variable on the bereavement indicator (Panel a), while in Panel (b), we include the interaction between the bereavement indicator and the respective adverse early life event (air raid/battlefield exposure and father absence) to test whether those elderly who have experienced such conditions are more or less resilient to bereavement. As discussed earlier, we expect more detrimental bereavement effects for those individuals who faced adverse early life conditions. Moreover, we test explicitly whether the sum of the main bereavement effect and the interaction effect of bereavement and early life conditions is significantly different from 0.[26]

In Subsection 3.4.1, we show the main results of our analysis and in Subsection 3.4.2, we conduct some sensitivity analyses, while in Subsection 3.4.3, we test for effect heterogeneity with respect to gender and socioeconomic status (SES).

3.4.1 Main Results

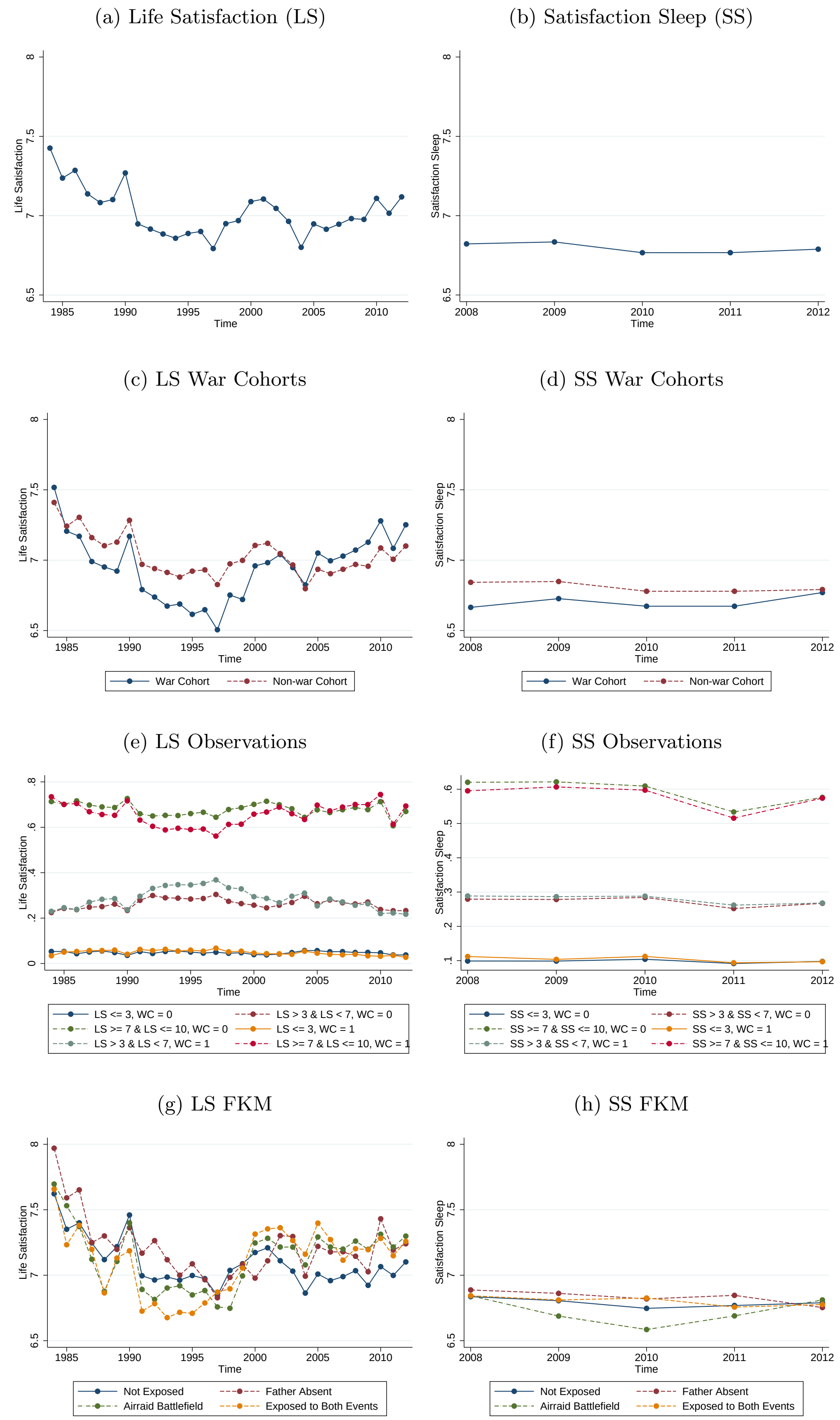
Tables 3.5 and 3.6 show the results for the mental health score MCS. As explained above the health module is only collected every other year, and therefore we can only consider the difference between 2012-2010 (Table 3.5). To further analyze the exact timing of bereavement within this

[24]We are thus not too worried that there is not enouough variation in our outcome variables, and most of our sample can suffer from a decrease or an increase in their satisfaction with life and sleep.

[25]We tested whether the difference is significant between each group for each year, but it is not.

[26]The results for these F-tests are shown in Appendix 3.B.

Figure 3.3: Outcome Variables in the SOEP



two wave interval, we split our adverse life event variable into two sub-indicators, as explained in Section 3.3.2 (Table 3.6).

Estimating an OLS regression of MCS on bereavement (Panel (a), Table 3.5), we find a significant negative bereavement effect on mental health for both samples.[27] The point estimates decrease and become insignificant when we control for time-invariant unobservables using the first difference approach. In Panel (b), we additionally include an interaction between the adverse early life condition and the bereavement event, for both OLS estimates the coefficients are now insignificant. However, the results of the first difference estimation indicate negative significant interaction effects. The magnitude of these significant effects is approximately half a standard deviation of the MCS variable.

Table 3.5: Results MCS 2010 - 2012

	Airraid Battlefield		**Father Absence**	
	OLS	Δ	OLS	Δ
Panel (a)				
Adverse Life Event 2012 - 2010	-2.974***	-1.837	-3.029***	-1.554
	1.128	1.182	1.129	1.158
N	5067	2105	5207	2161
R^2	0.006	0.002	0.006	0.002
Panel (b)				
Adverse Life Event 2012-2010	-1.745	0.564	-1.829	0.571
	1.549	1.523	1.459	1.405
Adverse Life Event 2012-2010 * EL Event	-2.787	-5.456**	-2.965	-4.876**
	2.228	2.299	2.258	2.296
N	5067	2105	5207	2161
R^2	0.006	0.006	0.007	0.005

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. EL stands for Early Life Event. The standard errors are clustered at the individual level.

Splitting the bereavement indicator with respect to the timing of the death in our first difference analysis, we find a negatively significant impact of approximately half a standard deviation of MCS for the second half of the two-year interval (Table 3.6, Panel (a)). Using this specification (Panel (b)), we also find a significant interaction of adverse early life circumstances and recent bereavement, which is even larger in absolute magnitude (more than one standard deviation). Our findings clearly indicate that the effect of bereavement on mental health occurs in the short

[27] The samples for the analysis of father absence and air raid/battlefield exposure differ slightly. Therefore, we display the results that do not include early life information for both samples separately.

run. We also test whether the sum of the main bereavement effect and the interaction effect of the early life event and bereavement is significant.[28] The bereavement effect for those who experienced adverse early life conditions is only significant in the case of recent (2012) losses. The magnitude of this effect is about double the treatment effect of the baseline regression in Table 3.6, Panel (a). This finding indicates that those born under adverse early life conditions are driving the results of the baseline specification.

Table 3.6: First Difference Results MCS

	(AB)	(FA)
Panel (a)		
Adverse Life Event 2011	0.558	0.832
	1.359	1.308
Adverse Life Event 2012	-5.557***	-5.474***
	1.968	1.974
N	2105	2161
R^2	0.007	0.007
Panel (b)		
Adverse Life Event 2011	1.182	0.823
	1.840	1.713
Adverse Life Event 2012	-0.485	0.132
	2.619	2.409
Adverse Life Event 2011 * Early Life Event	-1.438	0.071
	2.698	2.631
Adverse Life Event 2012 * Early Life Event	-10.739***	-11.887***
	3.448	3.373
N	2105	2161
R^2	0.013	0.014

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.7 shows the results for life satisfaction, which is surveyed in every SOEP wave and allows us to use the differences between 2011-2010 as well as 2012-2011 per individual. For both samples, the point estimate in Panel (a) decreases in absolute magnitude when the first difference approach is used instead of OLS. However, the bereavement effect stays weakly significant (10% level). The interaction between the respective early life condition and bereavement is again highly significant and amounts to more than half a standard deviation in magnitude. The F-tests in Table 3.19 show that the sum of main bereavement effect and the interaction effect is highly

[28]The results for these F-tests are shown in Appendix 3.B, Table 3.18.

significant.

Table 3.7: Results Life Satisfaction

	Airraid Battlefield		Father Absence	
	OLS	Δ	OLS	Δ
	Panel (a)			
Adverse Life Event	-0.637***	-0.386*	-0.637***	-0.335*
	0.201	0.202	0.197	0.197
N	5535	4646	5690	4771
Number of Clusters	2961	2543	3044	2614
R^2	0.004	0.004	0.004	0.003
	Panel (b)			
Adverse Life Event	-0.152	0.015	-0.342	0.111
	0.245	0.241	0.228	0.217
Adverse Life * EL Event	-1.050***	-0.882**	-0.729*	-1.096***
	0.399	0.401	0.414	0.403
N	5535	4646	5690	4771
Number of Clusters	2961	2543	3044	2614
R^2	0.006	0.006	0.005	0.006

Source: SOEP, own calculations.
Notes: The dependent variable is the life satisfaction in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. EL stands for Early Life Event. The standard errors are clustered at the individual level.

Table 3.8 displays the estimated treatment effects for sleep satisfaction. The results do not differ much when using a pooled OLS analysis compared to a first difference strategy. Without the early life interaction term, bereavement has a significantly negative impact on sleep satisfaction (Panel (a)). Including the interaction term (Panel (b)), bereavement is only significant in interaction with father's absence. Thus, there is some indication that grief has a more adverse impact on those who experienced father's absence for the satisfaction sleep, a measure that might capture stress in a more direct way than life satisfaction or general mental health. The order of magnitude (in standard deviations of the outcome variable) is nevertheless smaller for satisfaction sleep. The coefficient of the interaction between father's absence and bereavement is lower than half of a standard deviation of sleep satisfaction. The sum of the main bereavement effect and the interaction effect is significant for both adverse life events (see Table 3.20).

So far our findings suggest a stronger impact of bereavement for those who were exposed to air raids/combat actions or father's absence. Following Scholte et al. (2014), we calculate the fixed effects of this model from Tables 3.5, 3.7, 3.8, by $\hat{\alpha}_i = \bar{H}_i - \bar{X}_i{}'\hat{\beta}$ (see e.g., Wooldridge, 2010). In Tables 3.27, 3.28 and 3.29 we regress these fixed effects on an indicator for air raid/battlefield exposure or father's absence, and a range of background characteristics. The positive coefficient

Table 3.8: Results Satisfaction Sleep

	Airraid Battlefield		**Father Absence**	
	OLS	Δ	OLS	Δ
	Panel (a)			
Adverse Life Event	-0.565**	-0.566**	-0.549**	-0.510**
	0.223	0.234	0.217	0.228
N	5530	4641	5686	4767
Number of Clusters	2961	2542	3044	2613
R^2	0.003	0.002	0.003	0.002
	Panel (b)			
Adverse Life Event	-0.288	-0.292	-0.047	-0.108
	0.315	0.312	0.276	0.261
Adverse Life * EL Event	-0.601	-0.603	-1.243***	-0.990**
	0.445	0.467	0.427	0.470
N	5530	4641	5686	4767
Number of Clusters	2961	2542	3044	2613
R^2	0.004	0.003	0.005	0.003

Source: SOEP, own calculations.
Notes: The dependent variable is the sleep satisfaction in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. EL stands for Early Life Event. The standard errors are clustered at the individual level.

on air raid/battlefield exposure indicates that those exposed to adverse economic events during childhood, have higher mental health, higher life and sleep satisfaction. The negative coefficient on father's absence implies that those raised with an absent father have lower mental health, and lower life and sleep satisfaction. However all of these estimates are insignificant. Combining these results with the findings that there are seemingly no long-run effects from being exposed to air raid/battle field or an absent father during childhood (see Tables 3.30, 3.31 and 3.32) and the findings from Tables 3.5, 3.7, 3.8 (i.e., the effects of an adverse event later in life is magnified after these early life events), indicate that the effects of an absent father or an exposure to air raid/battlefield during early childhood primarily runs via the effect of the major adverse life events.

3.4.2 Sensitivity Analyses

Trimming Outcomes

For individuals who have a life (sleep) satisfaction of 0 or 10 in wave t-1, it is ex ante clear that the respective measure cannot decrease/increase any further from t-1 to t in response to the treatment. Therefore, we conduct a robustness check excluding these specific cases.[29] For life

[29] We drop all observations that have the highest or lowest possible score in (t-1) when calculating the first difference.

satisfaction (satisfaction sleep), we drop more than 200 (400) observations for this sensitivity analysis, leaving overall sample sizes of more than 4000 individuals for all analyses. Nevertheless as Tables 3.33 and 3.34 show, our results remain stable. We still observe a significant interaction effect on life satisfaction. For life satisfaction, the coefficients of both interaction terms gain in absolute magnitude compared to our main results, which is in line with our expectations. However, for satisfaction sleep, the significant coefficient on the interaction between bereavement and father's absence slightly decreases in absolute terms.

Excluding Cancer Deaths

In a next step, we investigate whether we find any indication of anticipation effects that might affect mental health before the actual death of a loved one.[30] The presence of anticipation effects is expected to downward bias our estimated bereavement effects. In the case of cancer, individuals are mostly informed about the increased risk to loose their partner in the future. Therefore, we conduct a robustness analysis excluding all cases for whom the cause of death is known to be cancer. Thereby, we loose approximately 20 observations for all our estimations.[31]

As expected, the significant interaction effects increase in absolute magnitude for the mental health summary score (MCS) once we focus on non-cancer deaths. Less anticipation effects lead to larger decreases in mental health due to a sudden death in addition to adverse early life conditions. For life satisfaction we still find weakly significant negative interaction effects. The interaction between bereavement and air raid/battlefield exposure gains in absolute magnitude compared to our main results. However, the point estimate of the interaction term for father absence decreases from -1.096 to -0.742 and remains only weakly significant.[32] While as expected, for satisfaction sleep, all point estimates increase in absolute magnitude after dropping the cancer death cases. Presumably sudden losses combined with adverse early life events decrease satisfaction sleep.

3.4.3 Effect Heterogeneity

In the following section, we test for heterogeneous treatment effects with respect to socioeconomic status (SES) and gender. We proxy high SES with high father's education. To investigate whether our results are heterogeneous in these two dimensions, we interact all our treatment

[30] For a detailed analysis of anticipation effects in the bereavement literature see e.g., Siflinger (2013).
[31] Tables 3.35, 3.36, 3.37, and 3.38 show the estimates using this restricted sample.
[32] We would like to emphasize that the amount of bereaved cases in our dataset is of course limited. Since dropping cancer deaths does involve an additional loss of treated observations, the loss of significance in some cases can be very well explained by the shrinkage of the treatment group.

indicators with SES/gender. This leads to the following two estimation equations derived from Equation (3.2):

$$\Delta H_{it} = (\Delta X_{it})^{'}\gamma + (\Delta D_{it})\beta_1 + (\Delta D_{it}E_i)\beta_2 + (\Delta D_{it}h_i)\beta_3 + (\Delta D_{it}E_ih_i)\beta_4 + \Delta u_{it} \tag{3.3}$$

where H_{it} is either life or sleep satisfaction, and h_i indicates whether or not the individual is a male or has high father's education. This will be slightly different when we analyze MCS:

$$\begin{gathered}\Delta H_{it} = (\Delta X_{it})^{'}\gamma + (\Delta D_{i(2011)})\delta_1 + (\Delta D_{i(2012)})\delta_2 + (\Delta D_{i(2011)}E_i)\delta_3 + (\Delta D_{i(2012)}E_i)\delta_4 + \\ (\Delta D_{i(2011)}h_i)\delta_5 + (\Delta D_{i(2012)}h_i)\delta_6 + (\Delta D_{i(2011)}E_ih_i)\delta_7 + (\Delta D_{i(2012)}E_ih_i)\delta_8 + \Delta u_{it}\end{gathered} \tag{3.4}$$

Additionally to the overall significance test of the bereavement effect, we investigate the overall bereavement effects separately for men/women and high/low SES groups. That is, we test whether $\beta_1 + \beta_2 = 0$ (significant overall effect of bereavement for baseline group, i.e., women or low SES group), whether $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 0$ (significant overall effect for heterogeneity group), and whether $\beta_1 + \beta_2 + \beta_3 + \beta_4 = \beta_1 + \beta_2$ (differential effect for the heterogeneity group) in the regressions of life and sleep satisfaction.[33] This procedure allows us to investigate whether the combination of bereavement and adverse early life circumstances has similar overall effects on both gender and/or both SES groups.

Moreover, by analyzing the triple interaction effect between bereavement, adverse early life conditions and SES/gender (i.e., the coefficients β_4, δ_7, δ_8), we show whether the role of early life conditions for the bereavement effect differs by gender or SES group.

Socioeconomic Status

Tables 3.9, 3.10, and 3.11 show the results for the mental health score (MCS), life and sleep satisfaction for high father's education.

Table 3.9 confirms the order of magnitude of the significant bereavement effects in our baseline specification (Table 3.6) for those with low SES. An F-test on the significance of the overall bereavement effect for people who experienced adverse early life circumstances (see Table 3.21,

[33]The tests are analogous for the case of MCS when we incorporate the timing of bereavement (2011, 2012)

Panel (b)) shows that the effect of bereavement (in 2012) is significantly negative and of similar magnitude for both, those with high and low SES. These effects are not statistically different (see last row, Table 3.21). We do not find a significant difference in the impact that early life circumstances have on the bereavement effect either for high father's education as δ_7 and δ_8 in Table 3.9 are not significant.[34]

Table 3.9: First Difference Results MCS Father's Education

	(AB)	(FA)
Panel (a)		
Adverse Life 2011	-0.699	-0.391
	1.404	1.374
Adverse Life 2012	-4.928**	-4.874**
	2.348	2.350
Adverse Life 2011 * High Father's Education	6.712	6.527
	4.222	4.216
Adverse Life 2012 * High Father's Education	-1.250	-1.147
	5.443	5.479
N	1917	1965
R^2	0.008	0.007
Panel (b)		
Adverse Life 2011	-0.294	-0.766
	1.916	1.687
Adverse Life 2012	-0.976	-1.745
	2.787	2.665
Adverse Life 2011 * High Father's Education	7.285	11.739**
	5.732	5.928
Adverse Life 2012 * High Father's Education	6.336	7.345
	6.233	6.258
Adverse Life 2011 * EL Event	-0.878	1.055
	2.793	2.860
Adverse Life 2012 * EL Event	-10.332**	-9.359**
	4.153	4.501
Adverse Life 2011 * EL * High Father's Education	-1.393	-9.504
	8.396	7.961
Adverse Life 2012 * EL * High Father's Education	-9.841	-10.949
	7.877	8.125
N	1917	1965
R^2	0.016	0.015

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. EL stands for Early Life Event. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

[34] We want to emphasize that these results might be driven by very small cell sizes. As already outlined, we have a limited number of bereavement cases. Therefore, one has to be cautious drawing conclusions from our heterogeneity analyses that add another level of interaction terms and thus further diminish the cell sizes.

For life satisfaction, the baseline bereavement effects in Panel (a) (Table 3.10) lose significance once we add the SES interaction term. However, the point estimate (for those with low SES) only decreases slightly in absolute terms compared to Table 3.7. The F-test of the bereavement effect for those with high SES (Table 3.22, Panel a) does not reject the null hypothesis either. In Panel (b), only the interaction between father's absence and bereavement stays weakly significant. The F-tests in Table 3.22, Panel (b), show that the bereavement effect for those who experienced adverse early life conditions is only significant in the case of low SES. The absolute magnitude of the effect is higher, but insignificant, for those with high SES. We do not find a significant difference between these effects for high/low SES (i.e., testing whether $\beta_3 + \beta_4 = 0$). As β_4 is insignificant but high in absolute magnitude, we cannot infer that the role of early life conditions for bereavement differs by SES.[35]

Table 3.10: First Difference Results Life Satisfaction Father's Education Interaction

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.339	-0.298
	0.224	0.219
Adverse Life Event * High Father's Education	0.067	0.026
	0.628	0.627
N	4221	4331
Number of Clusters	2315	2378
R^2	0.004	0.004
Panel (b)		
Adverse Life Event	-0.016	-0.015
	0.266	0.241
Adverse Life Event * High Father's Education	0.658	1.086
	0.574	0.450
Adverse Life Event * Early Life Event	-0.741	-0.827*
	0.457	0.487
Adverse Life Event * Early Life Event * High Father's Education	-1.088	-1.524
	1.165	1.034
N	4221	4331
Number of Clusters	2315	2378
R^2	0.007	0.007

Source: SOEP, own calculations.
Notes: The dependent variable is life satisfaction in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

For satisfaction sleep (Table 3.11), the point estimate of the interaction between adverse early life conditions and bereavement (for those with low SES) stays fairly similar compared to our

[35] As already mentioned above, these insignificant results may be driven by our small cell sizes.

main results. However, our estimation results suggest a (more than) balancing impact of father's education on the bereavement effect. The coefficient of the interaction term between bereavement and SES has a positive sign and is larger than the baseline effect of bereavement in absolute terms, in both panels. The F-tests in Table 3.23 show that the bereavement effect for those with adverse early life conditions is only significant for the subgroup with low SES. However, these effects for low versus high SES individuals are only significantly different (10% level) in the case of father absence (see last row, Table 3.23). Again β_4 is small and insignificant. Thus, our results do not suggest a heterogeneous role of early life conditions for the bereavement effect by SES on satisfaction sleep.

Table 3.11: First Difference Results Satisfaction Sleep Father's Education Interaction

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.670**	-0.598**
	0.272	0.266
Adverse Life Event * High Father's Education	1.096**	1.021**
	0.460	0.457
N	4216	4327
Number of Clusters	2313	2376
R^2	0.003	0.002
Panel (b)		
Adverse Life Event	-0.393	-0.248
	0.350	0.282
Adverse Life Event * High Father's Education	1.092**	1.228***
	0.520	0.433
Adverse Life Event * Early Life Event	-0.636	-1.022*
	0.549	0.602
Adverse Life Event * Early Life Event * High Father's Education	0.089	0.047
	0.912	0.885
N	4216	4327
Number of Clusters	2313	2376
R^2	0.003	0.004

Source: SOEP, own calculations.
Notes: The dependent variable is satisfaction sleep in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

Gender

Table 3.12 displays the results on mental health when we investigate gender differences. Tables 3.13 and 3.14 show the results with the gender interaction for life and sleep satisfaction. As outlined before, these results should be considered with caution because of the limited number of bereavement cases. We only find a significant effect of being male, having grown up with an absent father and bereavement in 2011 on mental health. Regarding the satisfaction outcomes, there is no significant gender difference in the role of early life events for bereavement effects.

The F-tests (Tables 3.24, 3.25, 3.26, Panel (b)) on the significance of the overall bereavement effects (i.e., testing whether the bereavement effect is equal to 0 for men/women who experienced adverse early life conditions) show significant effects for women. For men, the bereavement effect is only significant in the case of air raid/battlefield exposure on sleep satisfaction. The difference between these effects for men and women are only significant in the case of life/sleep satisfaction and the early life event of father's absence.

3.5 Conclusion

In this chapter, we analyze the joint impact of adverse early life conditions during World War 2 and bereavement on general mental health, sleep satisfaction, and life satisfaction. Our outcome variables cover a wide range of mental and stress-related disorders and are particularly relevant in the context of human wellbeing and productivity (see e.g., Rosekind et al., 2010). We provide a deeper understanding of resilience to bereavement and its determinants.

We use the SOEP, a German longitudinal survey, and a novel dataset on childhood in the (post) war context in Germany ("Frühe Kindheit im (Nach-)Kriegskontext" (FKM)). Using a first difference approach, we control for observed and unobserved time-invariant heterogeneity in our analysis.

Our findings suggest a stronger impact of bereavement for those who were exposed to air raids/combat actions or father's absence. We also showed that these results are reasonably robust as the exclusion of those individuals that cannot experience changes (increase or decrease) in their outcome variables as well as exclusion of cancer deaths do not change our conclusion.

The results of our analysis emphasize the importance of the early life environment for dealing with bereavement and grief late in life. We have shown that such traumatic events have also an indirect long run effect on mental health and wellbeing since they affect the magnitude of bereavement effects in late life. Along these lines, our findings underline the necessity of policy measures that prevent such adverse early life conditions and support children to deal with difficult circumstances.

Table 3.12: First Difference Results MCS Gender Interaction

	(AB)	(FA)
Panel (a)		
Adverse Life Event 2011	0.713	0.751
	1.709	1.627
Adverse Life Event 2012	-6.217***	-6.148***
	2.307	2.316
Adverse Life Event 2011 * Male	-0.428	0.233
	2.789	2.704
Adverse Life Event 2012 * Male	2.500	2.546
	4.342	4.344
N	2105	2161
R^2	0.007	0.007
Panel (b)		
Adverse Life Event 2011	0.122	-0.475
	2.313	1.965
Adverse Life Event 2012	-0.398	0.490
	3.488	3.120
Adverse Life Event 2011 * Male	2.983	4.297
	3.712	3.720
Adverse Life Event 2012 * Male	-0.264	-1.060
	4.998	4.754
Adverse Life Event 2011 * Early Life Event	1.500	3.448
	3.401	3.376
Adverse Life Event 2012 * Early Life Event	-11.181***	-12.758***
	4.111	3.911
Adverse Life Event 2011 * Early Life * Male	-8.126	-9.075*
	5.328	5.346
Adverse Life Event 2012 * Early Life * Male	2.150	3.773
	9.095	8.985
N	2105	2161
R^2	0.014	0.015

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.13: First Difference Results Life Satisfaction Gender Interaction

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.573**	-0.506*
	0.267	0.264
Adverse Life Event * Male	0.586	0.523
	0.368	0.358
N	4646	4771
Number of Clusters	2543	2614
R^2	0.005	0.004
Panel (b)		
Adverse Life Event	-0.139	0.087
	0.326	0.271
Adverse Life Event * Male	0.482	0.073
	0.422	0.444
Adverse Life Event * Early Life Event	-0.952*	-1.492***
	0.531	0.543
Adverse Life Event * Early Life Event * Male	0.225	1.157
	0.737	0.717
N	4646	4771
Number of Clusters	2543	2614
R^2	0.007	0.008

Source: SOEP, own calculations.
Notes: The dependent variable is the change in life satisfaction in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.14: First Difference Results Satisfaction Sleep Gender Interaction

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.800***	-0.753**
	0.309	0.303
Adverse Life Event * Male	0.733*	0.744***
	0.428	0.416
N	4641	4767
Number of Clusters	2542	2613
R^2	0.003	0.003
Panel (b)		
Adverse Life Event	-0.700*	-0.271
	0.405	0.321
Adverse Life Event * Male	1.274**	0.516
	0.548	0.537
Adverse Life Event * Early Life Event	-0.218	-1.212*
	0.624	0.641
Adverse Life Event * Early Life Event * Male	-1.199	0.615
	0.823	0.835
N	4641	4767
Number of Clusters	2542	2613
R^2	0.004	0.004

Source: SOEP, own calculations.
Notes: The dependent variable is Satisfaction sleep in the SOEP. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for exposure to air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

3.A Data Addendum

3.A.1 Description of the "Frühe Kindheit im (Nach-)Kriegskontext" (FKM)

[36] The FKM study is a cooperation between the DIW (Deutsches Institut für Wirtschaftsforschung) and Prof. Gerard J. van den Berg, PhD, and was conducted by TNS Infratest in the summer of 2012. Among the topics covered in this post-war survey are war and hunger exposure, pre- and postnatal environment, and the familial situation. The SOEP 2012 (subsamples A-H and J) is the basis for the FKM. In particular, the survey was conducted among those participants who were born in Germany between 1935 and 1950, including the former Eastern territories of the German Reich. Moreover individuals were excluded if there was no successful interview in the 2012 wave or if they refused to participate in the following wave (2013). The potential participants were first contacted by mail and together with a letter, they received a small gift (the book on post-war Germany by Reichardt and Zierenberg (2009)). The participants were interviewed on the phone (CATI). The adjusted sampling population includes 4,135 individuals of which 3,060 interviews were successfully completed.

3.A.2 Generating the Bereavement Indicators

Further Information on the Construction of Bereavement Variables

Our death indicators are constructed in the following steps; first, we merge the information of 2011 to 2012 and 2010 to 2011, generating two separate two-wave datasets. We generate these two wave datasets in order to treat each difference in a similar fashion. We can not tackle the initial conditions problem for the waves 2010-2011, and thus decided to treat the 2011-2012 wave in the exact same way. Second, we redefine the variables indicating death of the partner, the father, the child, the mother, or another household member. The redefinition is necessary since the time period indicated in the question wording does not correspond with the actual individual time frame between two waves. Specifically, the question refers to calendar time whereas our first difference strategy uses the difference between two interviews. In the raw data, the question in wave (t) about the death of a person covers the period from January 1 in year (t-1) until (t). Thus, the question in wave (t) covers partly the time before the wave (t-1) interview. To make sure the bereavement variables in wave (t) only cover the information from interview (t-1) to (t), we replace the respective death indicator in wave (t) with 0 if the death occurred before

[36] The description of the FKM follows two documents provided by TNS Infratest: Bohlender and Siegel (2012), TNSInfratest (2012).

the (t-1) interview. Analogously, we replace the indicator in wave (t-1) with 1 in that case (see Tables 3.15 and 3.16).

Adjustments for MCS estimations

We generate the 2012-2010 “change” in bereavement (ΔD_{health}) setting it equal to D for wave 2012. We then replace entries of ΔD_{health} for wave 2012 by 1 if D=1 in wave 2011 for the same individual (see Table 3.17). This is necessary in order to define the death indicator between the two waves consistently as the MCS is only surveyed biannually.

Table 3.15: Bereavement, 2010-2011

Occurrence/time of event				Derived variables					
2009	2010, before interview	2010, after interview	2011	D_{2010}	D_{2011}	$(D_{2011} - D_{2010})$	ΔD	Obs. MCS	Obs. Satisfaction
0	0	0	1	0	1	1	1	12	12
0	0	1	0	0	1	1	1	40	45
0	1	0	0	1	0	-1	.	13	14
1	0	0	0	1	0	-1	.	53	56
0	0	1	1	0	1	1	1	0	0
0	1	1	0	1	1	0	.	2	2
1	1	0	0	1	0	-1	.	0	0
0	1	0	1	1	1	0	.	0	0
1	0	0	1	1	1	0	.	0	0
1	0	1	0	1	1	0	.	0	0
0	1	1	1	1	1	0	.	0	0
1	1	1	0	1	1	0	.	0	0
1	1	0	1	1	1	0	.	0	0
1	0	1	1	1	1	0	.	0	0
1	1	1	1	1	1	0	.	0	0
0	0	0	0	0	0	0	0	1991	2100
Cases not providing month of death, death in 2011 wave							1	1	1
Cases not providing month of death, death in 2010 wave							.	1	1

Source: SOEP, own calculations.

Table 3.16: Bereavement, 2011-2012

Occurrence/time of event				Derived variables					
2010	2011, before interview	2011, after interview	2012	D_{2011}	D_{2012}	$(D_{2012} - D_{2011})$	ΔD	Obs. MCS	Obs. Satisfaction
0	0	0	1	0	1	1	1	5	6
0	0	1	0	0	1	1	1	28	32
0	1	0	0	1	0	-1	.	11	17
1	0	0	0	1	0	-1	.	55	73
0	0	1	1	0	1	1	1	0	0
0	1	1	0	1	1	0	.	3	3
1	1	0	0	1	0	-1	.	0	0
0	1	0	1	1	1	0	.	0	0
1	0	0	1	1	1	0	.	0	0
1	0	1	0	1	1	0	.	0	1
0	1	1	1	1	1	0	.	0	0
1	1	1	0	1	1	0	.	0	0
1	1	0	1	1	1	0	.	0	0
1	0	1	1	1	1	0	.	0	0
1	1	1	1	1	1	0	.	0	0
0	0	0	0	0	0	0	0	2009	2428
Cases not providing month of death, death in 2012 wave							1	1	1
Cases not providing month of death, death in 2011 wave							.	1	1

Source: SOEP, own calculations.

Table 3.17: Bereavement, 2010-2012

ΔD		Derived variables health			
2011	2012	ΔD_{health}	$\Delta D_{health,2011}$	$\Delta D_{health,2012}$	Observations
0	1	1	0	1	31
0	0	0	0	0	1958
1	0	1	1	0	0
1	1		case does not exist		0
.	0	0	0	0	51
.	1	1	0	1	3
0	.	.	0	.	2
1	.	1	1	0	53

Source: SOEP, own calculations.

3.A.3 Histograms of Outcome Variables

Figure 3.4: Histograms MCS

(a) MCS 2012 (b) First Difference MCS 2012

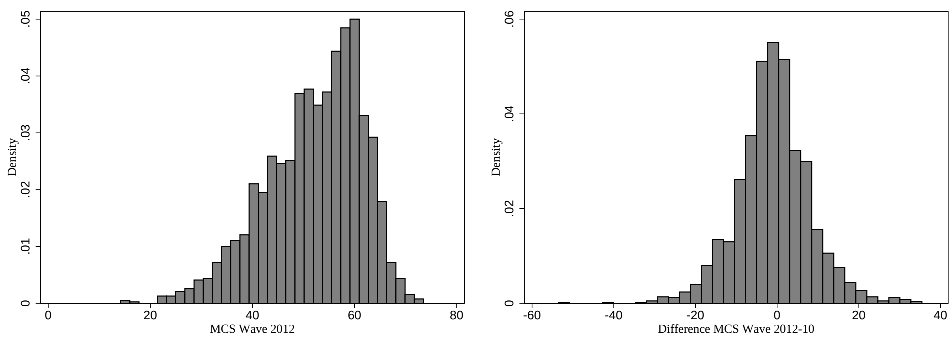
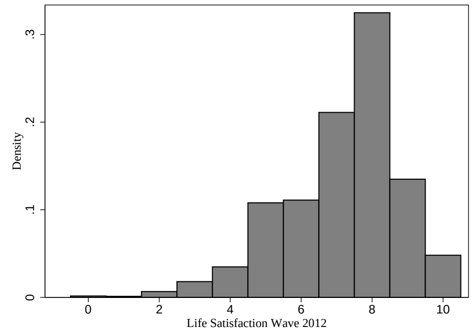
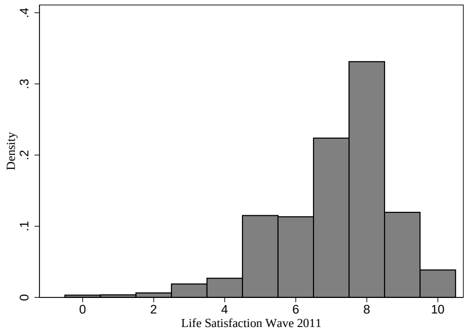


Figure 3.5: Histograms Satisfaction

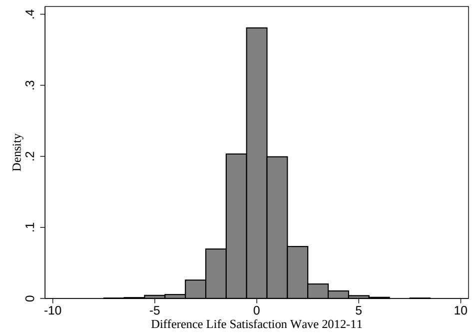
(a) Life Satisfaction 2012 (LS)



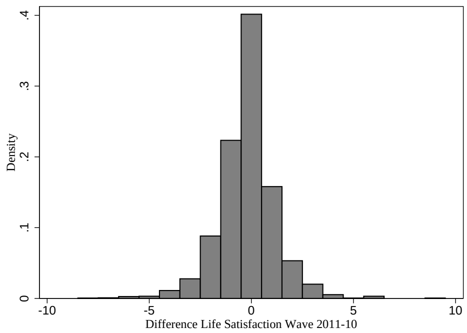
(b) Life Satisfaction 2011 (LS)



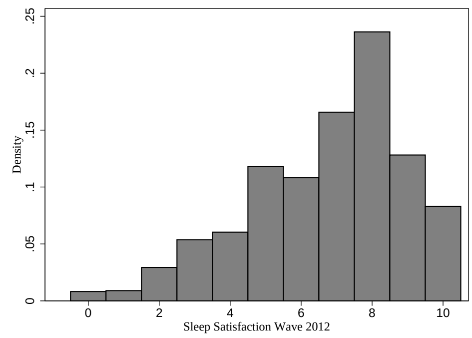
(c) First Difference LS 2012



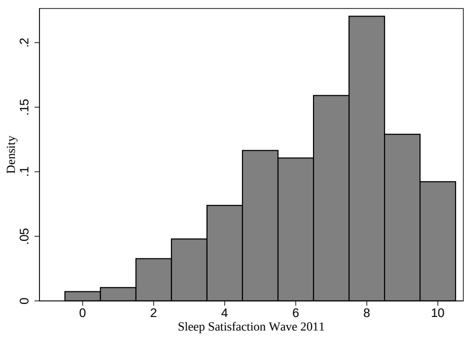
(d) First Difference LS 2011



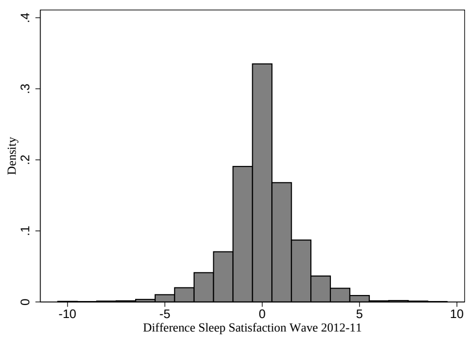
(e) Sleep Satisfaction 2012 (SS)



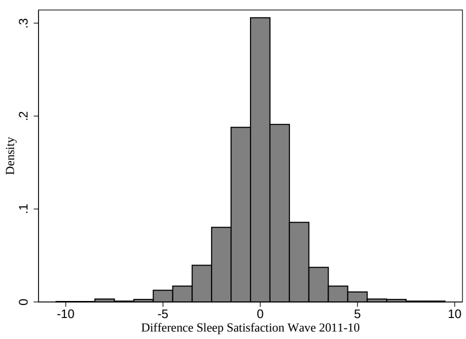
(f) Sleep Satisfaction 2011 (SS)



(g) First Difference SS 2012



(h) First Difference SS 2011



3.B F-tests

Table 3.18: Expected Changes MCS

t=	AB		FA	
	β	P-val.	β	P-val.
E[Δ MCS 2011 | EL = t]	-0.2560	0.8972	0.8937	0.6566
E[Δ MCS 2012 | EL = t]	-11.2243	0.0000	-11.7553	0.0000

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of MCS on AL and AL*EL and a quadratic in age. The expected changes (β) are calculated as the sum of the estimated AL effect and the estimated interaction effect between AL and EL. The P-Values result from conducting an F-test on whether the sum of the respective coefficient (β) is significantly different from 0.

Table 3.19: Expected Changes Life Satisfaction

t=	AB		FA	
	β	P-val.	β	P-val.
E[Δ Life S. | EL = t]	-0.8667	0.0072	-0.9853	0.0038

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of life satisfaction on AL and AL*EL and a quadratic in age. The expected changes (β) are calculated as the sum of the estimated AL effect and the estimated interaction effect between AL and EL. The P-Values result from conducting an F-test on whether the sum of the respective coefficient (β) is significantly different from 0.

Table 3.20: Expected Changes Satisfaction Sleep

t=	AB		FA	
	β	P-val.	β	P-val.
E[Δ Sleep S. | EL = t]	-0.8954	0.0101	-1.0977	0.0051

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of sleep satisfaction on AL and AL*EL and a quadratic in age. The expected changes (β) are calculated as the sum of the estimated AL effect and the estimated interaction effect between AL and EL. The P-Values result from conducting an F-test on whether the sum of the respective coefficient (β) is significantly different from 0.

Table 3.21: Expected Changes MCS, High Father's Education (HFE)

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ MCS | AL 2011, HFE = 1]	6.013	0.1321	6.1363	0.1248
E[Δ MCS | AL 2012, HFE = 1]	-6.178	0.2093	-6.0214	0.2248
Panel (b)				
E[Δ MCS | AL 2011, HFE = 1, EL = t]	4.7204	0.4157	2.5233	0.5986
E[Δ MCS | AL 2012, HFE = 1, EL = t]	-14.8130	0.0001	-14.7084	0.0001
E[Δ MCS | AL 2011, LFE = 1, EL = t]	-1.1719	0.5657	0.2891	0.9010
E[Δ MCS | AL 2012, LFE = 1, EL = t]	-11.3078	0.0003	-11.1043	0.0023
$\delta_5 + \delta_7$ 2011	5.8923	0.3371	2.2343	0.6743
$\delta_6 + \delta_8$ 2012	-3.5052	0.4679	-3.6041	0.4875

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of MCS on AL and AL*EL, the interactions with father's education (high HFE and low LFE) and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

Table 3.22: Expected Changes Life Satisfaction, HFE

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ Life S. | HFE = 1]	-0.272	0.6432	-0.2717	0.6446
Panel (b)				
E[Δ Life S. | HFE = 1, EL = t]	-1.1874	0.2079	-1.2799	0.1228
E[Δ Life S. | LFE = 1, EL = t]	-0.7574	0.0419	-0.8420	0.0468
$\beta_3 + \beta_4$	-0.4300	0.6712	-0.4380	0.6379

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of life satisfaction on AL and AL*EL, the interactions with father's education (high HFE, low LFE), and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

Table 3.23: Expected Changes Satisfaction Sleep, HFE

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ Sleep S. | HFE = 1]	0.425	0.2539	0.4230	0.2563
Panel (b)				
E[Δ Sleep S. | HFE = 1, EL = t]	0.1516	0.8072	0.0048	0.9931
E[Δ Sleep S. | LFE = 1, EL = t]	-1.0291	0.0151	-1.2702	0.0172
$\beta_3 + \beta_4$	1.1807	0.1153	1.2750	0.0985

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of sleep satisfaction on AL and AL*EL, the interactions with father's education (high HFE and low LFE), and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

Table 3.24: Expected Changes MCS, Gender

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ MCS | AL 2011, Male = 1]	0.285	0.8977	0.9838	0.6510
E[Δ MCS | AL 2012, Male = 1]	-3.718	0.3133	-3.6012	0.3283
Panel (b)				
E[Δ MCS | AL 2011, Male = 1, EL = t]	-3.5220	0.2271	-1.8044	0.5037
E[Δ MCS | AL 2012, Male = 1, EL = t]	-9.6925	0.1833	-9.5543	0.1876
E[Δ MCS | AL 2011, Female = 1, EL = t]	1.6215	0.5164	2.9730	0.2805
E[Δ MCS | AL 2012, Female = 1, EL = t]	-11.5783	0.0000	-12.2675	0.0000
$\delta_5 + \delta_7$ 2011	-5.1434	0.1791	-4.7773	0.2141
$\delta_6 + \delta_8$ 2012	1.8858	0.8040	2.7132	0.7219

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of MCS on AL and AL*EL, the interactions with gender, and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

Table 3.25: Expected Changes Life Satisfaction, Gender

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ Life S. | Male = 1]	0.013	0.9580	0.0178	0.9416
Panel (b)				
E[Δ Life S. | Male = 1, EL = t]	-0.3847	0.3756	-0.1751	0.5683
E[Δ Life S. | Female = 1, EL = t]	-1.0912	0.0095	-1.4049	0.0029
$\beta_3 + \beta_4$	0.7065	0.2426	1.2298	0.0289

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of life satisfaction on AL and AL*EL, the interactions with gender, and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

Table 3.26: Expected Changes Satisfaction Sleep, Gender

t=	AB		FA	
	β	P-val.	β	P-val.
Panel (a)				
E[Δ Sleep S. | Male = 1]	-0.068	0.8205	-0.0092	0.9746
Panel (b)				
E[Δ Sleep S. | Male = 1, EL = t]	-0.8443	0.0320	-0.3527	0.2657
E[Δ Sleep S. | Female = 1, EL = t]	-0.9185	0.0533	-1.4836	0.0077
$\beta_3 + \beta_4$	0.0741	0.9040	1.1309	0.0767

Source: SOEP, own calculations.

Notes: These are the expectations calculated from a first difference regression of sleep satisfaction on AL and AL*EL, the interactions with gender, and a quadratic in age. Panel (a) does not include the interactions with EL. The expected changes (β) are calculated as the sum of the respective estimated main and interaction effects. The P-Values result from conducting an F-test on whether the sum of the respective coefficients (β) is significantly different from 0.

3.C Fixed Effects and Level Regressions

Table 3.27: Fixed Effects regressed on EL (Levels LS)

	(AB)	(FA)
Early Life Event	0.0148	-0.0244
	(0.0378)	(0.0289)
Males	0.0738***	0.0797***
	(0.0257)	(0.0254)
High Father Education	0.0276	0.0394
	(0.0306)	(0.0303)
Age (in months)	-0.00443	-0.00592
	(0.00789)	(0.00761)
Age^2 (in months)	0.00000267	0.00000367
	(0.00000476)	(0.00000462)
Constant	2.285	2.776
	(3.252)	(3.121)
N	4695	4825

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

Table 3.28: Fixed Effects regressed on EL (Levels SS)

	(AB)	(FA)
Early Life Event	0.00412	-0.0709*
	(0.0491)	(0.0376)
Males	-0.0592*	-0.0874***
	(0.0334)	(0.0331)
High Father Education	0.0299	0.0237
	(0.0399)	(0.0396)
Age (in months)	0.00588	0.0125
	(0.0103)	(0.00990)
Age^2 (in months)	-0.00000348	-0.00000738
	(0.00000619)	(0.00000601)
Constant	-2.596	-5.416
	(4.228)	(4.064)
N	4689	4819

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

Table 3.29: Fixed Effects regressed on EL (Levels MCS)

	(AB)	(FA)
Early Life Event	0.654	-0.536
	(0.611)	(0.465)
Males	-0.224	-0.245
	(0.406)	(0.405)
High Father Education	0.522	0.638
	(0.479)	(0.479)
Age (in months)	-0.0661	-0.0465
	(0.129)	(0.125)
Age^2 (in months)	0.0000376	0.0000294
	(0.0000772)	(0.0000751)
Constant	28.80	17.36
	(53.48)	(51.45)
N	1931	1981

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

Table 3.30: Effects of EL on LS (Levels)

	(AB)	(FA)
Early Life Event	0.0492	0.0307
	(0.0642)	(0.0488)
Males	0.167***	0.180***
	(0.0438)	(0.0435)
Age (in months)	0.0127	0.0148
	(0.0135)	(0.0130)
Age^2 (in months)	-0.00000793	-0.00000917
	(0.00000813)	(0.00000791)
Constant	2.007	1.146
	(5.555)	(5.354)
N	5535	5690

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

Table 3.31: Effects of EL on SS (Levels)

	(AB)	(FA)
Early Life Event	0.00579	0.0882
	(0.0871)	(0.0661)
Males	0.496***	0.537***
	(0.0594)	(0.0589)
Age (in months)	0.0320*	0.0283
	(0.0183)	(0.0177)
Age^2 (in months)	-0.0000202*	-0.0000183*
	(0.0000110)	(0.0000107)
Constant	-6.022	-4.350
	(7.535)	(7.259)
N	5530	5686

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

Table 3.32: Effects of EL on MCS (Levels)

	(AB)	(FA)
Early Life Event	0.424	-0.171
	(0.387)	(0.293)
Males	2.330***	2.309***
	(0.262)	(0.260)
Age (in months)	0.336***	0.366***
	(0.0802)	(0.0777)
Age^2 (in months)	-0.000205***	-0.000222***
	(0.0000484)	(0.0000471)
Constant	-86.06***	-99.23***
	(33.08)	(31.88)
N	5067	5207

Source: SOEP and FKM, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. AB stands for air raid/battlefield exposure, and FA for father's absence. Standard errors in parentheses.

3.D Sensitivity Analysis

Table 3.33: Results Life Satisfaction exlcude 0, 10

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.435**	-0.381*
	0.215	0.209
N	4425	4542
Number of Clusters	2478	2545
R^2	0.005	0.004
Panel (b)		
AL Event	-0.001	0.092
	0.254	0.232
Adverse Life Event * Early Life Event	-0.960**	-1.152***
	0.427	0.425
N	4425	4542
Number of Clusters	2478	2545
R^2	0.007	0.007

Source: SOEP, own calculations.
Notes: The dependent variable is life satisfaction and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield exposure, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.34: Results Satisfaction Sleep exlcude 0, 10

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.435**	-0.384*
	0.220	0.213
N	4169	4281
Number of Clusters	2383	2448
R^2	0.001	0.001
Panel (b)		
Adverse Life Event	-0.152	-0.036
	0.296	0.259
Adverse Life Event * Early Life Event	-0.614	-0.850**
	0.435	0.430
N	4169	4281
Number of Clusters	2383	2448
R^2	0.002	0.002

Source: SOEP, own calculations.
Notes: The dependent variable is satisfaction sleep and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.35: Results MCS No Cancer

	(AB)	**(FA)**
Panel (a)		
Adverse Life Event 2012 - 2010	-1.234	-0.894
	1.318	1.297
N	2085	2140
R^2	0.001	0.001
Panel (b)		
Adverse Life Event 2012 - 2010	1.497	1.643
	1.666	1.522
Adverse Life Event * Early Life Event	-6.718***	-6.214**
	2.510	2.567
N	2085	2140
R^2	0.006	0.005

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield exposure, and FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.36: Results MCS No Cancer

	(AB)	(FA)
Panel (a)		
Adverse Life Event 2011	0.576	0.982
	1.487	1.440
Adverse Life Event 2012	-4.085*	-3.998*
	2.320	2.329
N	2085	2140
R^2	0.003	0.003
Panel (b)		
Adverse Life Event 2011	1.601	1.314
	2.090	1.984
Adverse Life Event 2012	1.332	2.238
	2.724	2.301
Adverse Life 2011 * Early Life Event	-2.560	-0.788
	2.818	2.804
Adverse Life 2012 * Early Life Event	-12.745***	-14.691***
	3.906	3.808
N	2085	2140
R^2	0.010	0.011

Source: SOEP, own calculations.
Notes: The dependent variable is the mental health score (MCS) and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield exposure, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.37: Results Satisfaction Life No Cancer

	(AB)	(FA)
Panel (a)		
Adverse Life Event	-0.292	-0.262
	0.210	0.204
N	4626	4750
Number of Clusters	2530	2600
R^2	0.003	0.002
Panel (b)		
Adverse Life Event	0.119	0.016
	0.247	0.238
Adverse Life Event * Early Life Event	-0.956**	-0.742*
	0.419	0.427
N	4626	4750
Number of Clusters	2530	2600
R^2	0.005	0.003

Source: SOEP, own calculations.
Notes: The dependent variable is the life satisfaction and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield exposure, while FA stands for father's absence. The standard errors are clustered at the individual level.

Table 3.38: Results Satisfaction Sleep No Cancer

	(AB)	**(FA)**
Panel (a)		
Adverse Life Event	-0.727***	-0.681**
	0.272	0.264
N	4621	4746
Number of Clusters	2529	2599
R^2	0.003	0.002
Panel (b)		
Adverse Life Event	-0.395	-0.289
	0.347	0.294
Adverse Life Event * Early Life Event	-0.771	-1.043*
	0.547	0.564
N	4621	4746
Number of Clusters	2529	2599
R^2	0.003	0.004

Source: SOEP, own calculations.
Notes: The dependent variable is the sleep satisfaction and as estimation strategy we used first differences. The reported regressions include a quadratic in age (calculated in months) and a constant. AB stands for air raid/battlefield exposure, while FA stands for father's absence. The standard errors are clustered at the individual level.

Chapter 4

Coworkers, Networks and Job Search Outcomes[1]

4.1 Introduction

The job matching process is complicated by an enormous degree of heterogeneity between the workers and the jobs. Information about suitable jobs are not always available and the worker's productivity is usually unknown ex-ante. Personal relationships, informal contacts, and social networks potentially play a big role in overcoming these informational difficulties in the labor market both for firms and job seekers. Early studies on the networks in the labor market state that about 50% of workers find their jobs through friends, family members, and/or co-workers (see e.g., Holzer (1988), Montgomery (1991)). These findings are also in line with recent trends. According to Jobvite, an online recruiting platform, the top source of job applications are job boards (42.9%) and career sites (32.1%). However, the main source of hiring shifts to employment are referral programs which generate 39.9% of all hires.[2]

Given the significance of the social networks in the labor market, there has been a growing interest in understanding how social networks operate in the labor market. In particular, both the theoretical and the empirical literature have been expanding since the pioneering studies by Rees (1966) and Granovetter (1973).[3]

[1]This chapter is co-authored with Perihan O. Saygin and Andrea Weber.
[2]These statistics are based on data from 2007 to 2013 on a sample of firms that are Jobvite customers. See http://recruiting.jobvite.com/resources/recruiting-data-employment-statistics-by-jobvite-index/ (01.04.2013).
[3]See for example Montgomery (1991) or Ioannides and Loury (2004) for comprehensive surveys.

Looking at the existing literature, there are three perspectives of taking a look at the social networks in the labor markets: the job seeker side, the firm side and the social costs. Job seekers can use social networks to minimize their search costs by obtaining information about vacancies from the employed network members, while firms use referrals when hiring, as a signal for unknown productivity. Finally, if firms rely on networks to fill vacancies and if individuals rely on networks to find jobs, inequalities between different groups in the labor market can be fostered and can grow depending on the initial differences in the network employment rates (Calvo-Armengol and Jackson, 2004). Therefore social networks might also explain inequalities or poverty traps (Zenou, 2014).

Jackson (2010) classifies theoretical studies under two headlines. The first group of studies is based on models which use referrals as a signal for unknown productivity of the potential hirings. The pioneering model of this strand is Montgomery (1991) and focuses on employee selection. Firms recruit new workers who are connected to their productive workers. Therefore, the characteristics of incumbent members are relevant for the job search outcomes and similar type workers refer each other.

The second group of theoretical papers mostly provide models of information transmission in social networks (Calvo-Armengol and Jackson, 2004). In these models, networks consists of employed and unemployed workers and members randomly receive information about job opportunities. The unemployed workers keep the information for themselves while the employed workers pass the information on to their network members if they can not use this information. Calvo-Armengol and Jackson (2004) suggest that unemployed workers who are connected in a social network with a high employment rate are more likely to find a job and should earn higher wages. In addition, they compare two groups with different employment rates and suggest that lower employment rates within a group will lead to a higher drop-out rate which will eventually cause a persistent inequality between two groups. Finally, they also show that unemployment exhibits duration dependence. Similarly, according to Loury (2006), workers are likely to earn higher wages if their contacts have good connections, are employed, receive higher wages, and help the employer by reducing the uncertainty about the productivity of the job seeker.

Empirical studies use quite heterogeneous data sources and various social network definitions. Some studies analyze the social networks concerning the residential proximity using census data such as Topa (2001) and Bayer et al. (2008) while others consider the social ties like family and friends using survey data such as Magruder (2010), Kramarz and Nordstrom Skans (2013), and Cappellari and Tatsiramos (2010). Dustmann et al. (2011) for example use ethnicity based networks to show the network effects in the labor market. Using various definitions of social networks, it seems that there is a robust consensus that workers benefit from informal contacts when looking for a job and that social networks have a positive effect on the job finding rate.[4] Some of these studies also elaborate the effect of using networks on the quality of the subsequent matches (such as tenure and/or wage) with no clear consensus on the direction of the effect.

Some recent papers provide evidence for the effect of social networks consisting of past co-workers on the job search: Cingano and Rosolia (2012), Glitz (2013) and Hensvik and Skans (2013).[5] Cingano and Rosolia (2012) use matched employer-employee data for two Italian provinces over the period 1975 to 1997 and estimate the effect of the network employment rate on unemployment duration. In order to overcome the selection bias into unemployment, they use firm closures and find that one standard deviation increase in the network employment rate leads to an 8% reduction in unemployment duration. On the other hand, they only consider the displaced workers who find a job after the firm closure in order to analyze the unemployment duration. By using only the completed unemployment spells, they drop around 20% of the displaced workers from their sample. In other words, they condition on the outcome of becoming re-employed. Glitz (2013) follows the same approach in terms of network definitions and empirical specification with two distinctive features from Cingano and Rosolia (2012). First, Glitz (2013) uses an administrative dataset for German workers in the 4 largest metropolitan areas where observations are recorded only annually. The second feature is that mass layoffs are used as an exogenous variation to the network employment rate as an additional identification strategy. As a result, Glitz (2013) finds a strong positive effect of the network employment rate on re-

[4]See for example, Corcoran et al. (1980); Holzer (1988); Mortensen and Vishwanath (1994); Pistaferri (1999); Topa (2001); Calvo-Armengol and Jackson (2004); Kramarz and Nordstrom Skans (2013); Bayer et al. (2008); Dustmann et al. (2011); Laschever (2009); Pellizzari (2010); Cappellari and Tatsiramos (2010); Cingano and Rosolia (2012); Goel and Lang (2009); Glitz (2013); Beaman (2012). Most of the studies use survey data where employees are asked about how they found their job in order to compare the jobs obtained through social networks and with those found through formal methods. Pistaferri (1999) uses the Bank of Italy Survey of Household Income and Wealth where applicants are asked how they found their jobs. He reports a positive effect of using informal connections on job offer arrival rates but a negative effect on earnings. Similarly, Bentolila et al. (2004) provide evidence for a positive effect on the job finding but negative effect on earnings. They show that the social networks might induce mismatches between workers' productive advantage and their actual occupational choice using the "Multi-City Study of Urban Inequality, 1992-1994" survey. Antoninis (2006) suggests that the wage effect can be positive or negative depending on the type of tie. In particular, if the referee has a direct knowledge of the worker's productivity, new recruits receive a higher starting wage. From the firm side, the literature is scarce and a few papers agree that firms do not benefit from using social networks if workers are not properly incentivized (Kramarz and Thesmar (2013) and Beaman and Magruder (2012)).

[5]Hensvik and Skans (2013) use matched data from Swedish administrative employment registers and define social networks as past co-workers but analyze referral hirings rather than job search. They empirically test the implications of the model of Montgomery (1991) and show that firms use social networks as a signal of the worker's productivity, and that workers therefore benefit from the quality of their social networks.

employment probabilities after displacement and no significant effect on wages.

Despite the growing literature and interest in empirical tests of the social network theories, there is limited evidence on the channels through which social networks affect the job search outcomes. Our aim is to test whether the co-worker network is important for the job finding rate and the wage at the new job. Similar to the literature (see e.g., Cingano and Rosolia (2012) and Glitz (2013)) we define the social networks as the group of past co-workers building on a 5 year history. But in contrast to Cingano and Rosolia (2012) and Glitz (2013) we incorporate every worker displaced due to a firm closure using the Austrian Social Security Database (ASSD). The ASSD provides daily information on the universe of private sector workers covered by the social security system in Austria between 1980 and 2009. In order to analyze the effect of the network characteristics on the re-employment probability and the unemployment duration, we apply both a linear probability and a duration model in order to keep every displaced worker. In particular, we aim to distinguish between potential channels through which networks affect the job search outcome. Therefore, we investigate two dimensions of the co-worker network: the individual level and the firm level. At the individual level, we analyze the effect of the past co-worker network characteristics on the job search outcomes. To disentangle the different channels at work, we incorporate firm heterogeneity measures into the past co-worker network by decomposing the network employment rate according to firm characteristics. Furthermore we investigate whether former co-workers with similar characteristics are more profitable for the job finding rate. At the firm level, we elaborate whether firms are more likely to hire a displaced worker from the social network of their incumbent employees.

Our individual level results show that the higher the share of employed past co-workers the higher is the job-finding rate of the displaced worker. Past co-workers, that are employed in the same industry and in firms that are currently hiring, are particularly helpful. We also provide evidence for heterogeneity in the network effects - past co-workers with similar characteristics are important for some groups based on gender, age groups and occupation. The effect of the network characteristics on the wage growth (from job loss to re-entry wage) is inconclusive, despite the significant positive effect of former co-workers working at high wage firms. At the firm level, we find that 25% of the displaced workers find a new job in a connected firm. Furthermore, displaced workers with a link to the connected firm are three times as likely to be hired as similar workers from the same closing firm without a link to the connected firm.

The rest of the chapter is organized as follows; first, we give a brief description of the data and the sample selection process as well as the network formation process in Section 4.2. It also provides definitions of the firm closures, the displaced worker sample, the network characteristics and the job search outcomes of interest. Furthermore we provide a descriptive analysis of the displaced workers' characteristics, employment histories and network characteristics as well as the firms' characteristics where the network members are employed. Section 4.3 presents the empirical specification and the results. Finally, Section 4.4 concludes.

4.2 Data and Network Definitions

The empirical analysis is based on the Austrian Social Security Database (ASSD), which covers the universe of private sector workers in Austria over the years 1972-2012 (Zweimüller et al., 2009). The data provide detailed daily information on employment, unemployment, and other states relevant for social security such as sickness, retirement, or maternity leave. Earnings paid by each employer are recorded at an annual level. The matched employer-employee structure of the ASSD is defined by employer identifiers, which are linked to individual employment spells. To measure workforce characteristics at the firm level, we organize the data in a quarterly panel, collapsing it along employer identifiers. Firm exit dates are then defined as the last quarter date in which a firm employs at least one worker. We use a worker-flow approach to distinguish firm closures from other exit events such as mergers or institutional changes in the employer identifier. This approach is explained in detail in Fink et al. (2010).[6]

Our sample of displaced workers consists of individuals displaced by firms closing over the years 1980 - 2007. We make three restrictions to this sample. First, we only consider blue collar and white collar workers, who were still employed in the final quarter of firm existence, i.e., the quarter of the closure date. Second, we restrict the sample to workers with at least one year tenure at the closing firm. Third, we focus on workers who are between 20 and 55 years of age at displacement. The resulting sample includes 151,432 workers from 27,635 closing firms, which means that on average we observe 5.4 workers displaced by the same closing form.

[6]The main definition is that a closure is restricted to the exit of an employer identifier where less than 50% of the last year's workforce jointly move to the same new employer identifier. Because this approach is not meaningful for very small firms, we restrict closures to firms with at least 5 employees in the last year.

In comparison to the literature, Glitz (2013) uses establishment closures in the Hamburg, Cologne, Frankfurt and Munich metropolitan areas in 1995 and 1996. This leaves him with 10,916 displaced males from 1,814 establishments. While Cingano and Rosolia (2012) have 9,121 re-employed individuals displaced by 1,195 manufacturing firm closures with a focus on two Italian provinces (Treviso and Vicenza) from 1980 until 1994.[7] We thus have a larger sample of closing firms and displaced individuals all over Austria.

Co-Worker Networks

For each displaced worker the social network is defined as the set of all individuals who shared a workplace with her over the last five years before the firm closure date. Thereby we require that the employment spells of the contacts overlap for at least 30 days. We further exclude links with former co-workers that were established in very large firms with more than 3000 employees. This restriction facilitates computational tractability and excludes large networks, which encompass very limited information about interpersonal information flows. Finally, we also exclude co-displaced workers, who were displaced by the same closing firm of the network. These workers will form the comparison group at the closing firm level.

Table 4.1 presents summary statistics of individual and network characteristics of our sample of displaced workers. The average age of displaced workers is 36.8, a share of 41% are females, 91% are of Austrian nationality, and 53% have a blue collar contract before displacement. The average tenure of displaced workers at the closing firm, 4.87 years, is below the window length of the network definition. The median tenure is even shorter with 2.9 years. The average number of job changes within the last five years is 1.92 with a slightly larger median of 2 job changes. The average number of unemployment days is 50.3.

Due to the relatively high job turnover rate of displaced workers before displacement the size of their networks is relatively large. The average size of the co-worker network includes 158 contacts, the median is more moderate with 44 members. Note that the co-displaced workers, whom we remove from the network are in general only a small fraction of all contacts (average 5/158).

[7] In contrast to our displaced worker sample, the displaced workers of Cingano and Rosolia (2012) have to be employed in the closing firm in the last month of activity.

Table 4.1: Summary Statistics: Displaced Workers

	Mean	Median	Std. Dev.
Individual Characteristics			
Female	0.41		0.49
Age	36.8	36.0	9.5
Blue Collar Worker	0.53		0.50
Austrian Nationality	0.91		0.28
Tenure (in years)	4.87	2.92	4.84
Employed over Last 5 Years	4.27	4.90	1.06
Unemployed over Last 5 Years	0.14	0.00	0.35
Av. Number of Firms over Last 5 Years	1.92	2.00	1.20
Average Firm Size over Last 5 Years	50.29	19.28	105.4
Network Characteristics			
Network Size	158.3	44	339.0
Share Female	0.40	0.34	0.31
Share Blue Collar	0.62	0.76	0.35
Share Austrian	0.92	0.96	0.11
Share of Same Gender	0.68	0.75	0.27
Share in Same Age Group	0.28	0.25	0.18
Share of Same Occupation	0.69	0.81	0.31
Share of Same Nationality	0.86	0.95	0.23
Network Employment Rate			
Share Employed	0.56	0.57	0.18
Share Employed in Same Industry	0.19	0.13	0.19
Share Employed at Net Hiring Firms	0.24	0.21	0.18
Share Employed at Above Med. Wage Firms	0.30	0.26	0.21
Observations	151,432		

Source: ASSD, own calculations.

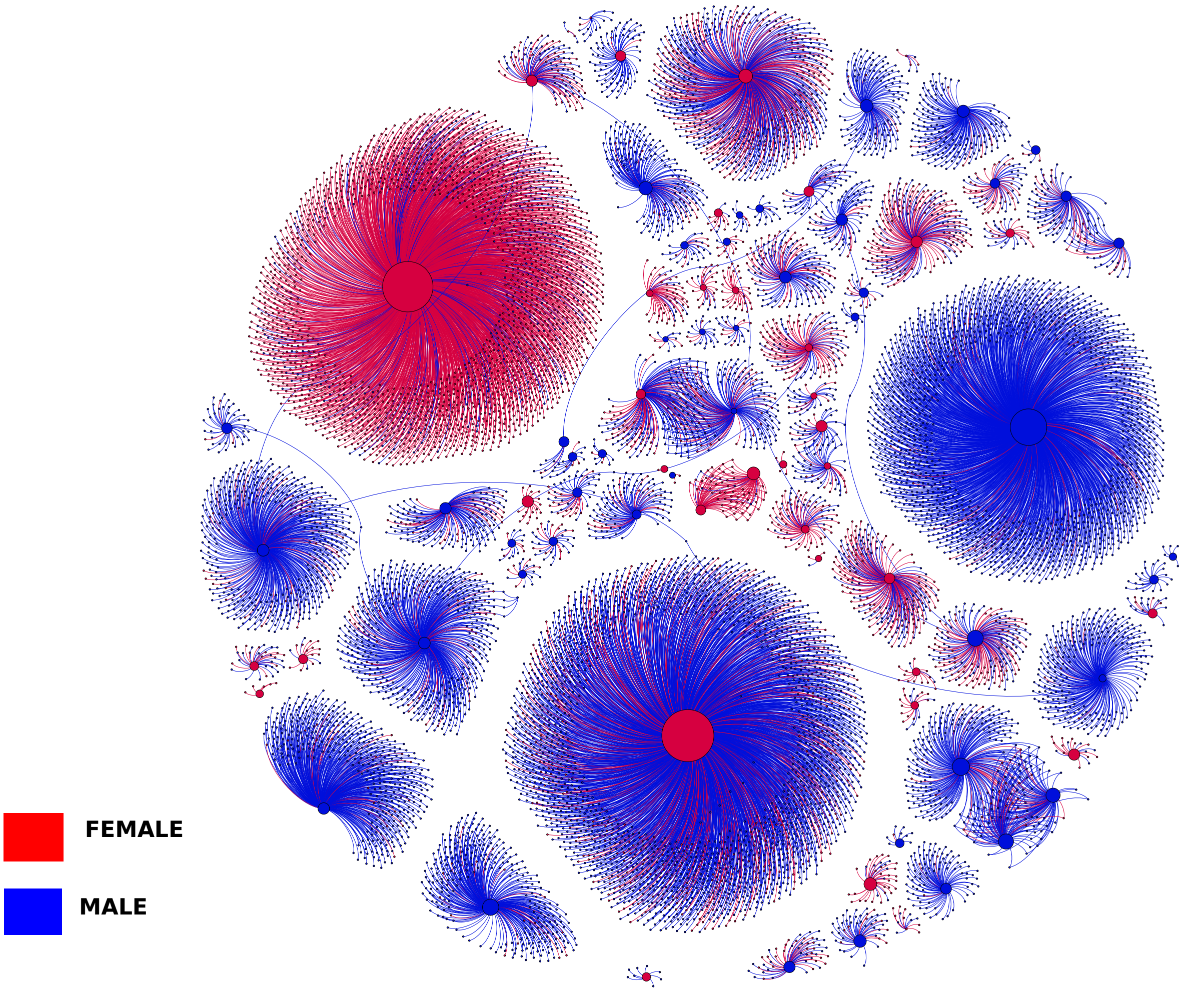
The characteristics of former co-worker in the network are quite heterogeneous: on average about 40% of network members are female, a share of 62% are blue collar workers, and a share of 92% are Austrian. If we compare the displaced workers with their network members we see that about 68% have the same gender, and 86% are of the same nationality as the displaced workers. 69% are the same job type and 28% in the same age group, where we split displaced workers into four age groups of about equal size. At the time of firm closure on average 56% of the network members hold a job (similar to Glitz (2013), lower than Cingano and Rosolia (2012)).[8] If we compare the industry of the closing firm with the industries in the firms where network members are employed, we find that only 19% of the contacts overlap. To classify industries we use a two digit NACE classification, which covers about 50 different industries. 24% of the employed network members work at a hiring firm, while 30% of the employed network members work at an above the median wage paying firm.

Figure 4.1 shows an example of the structure of the co-worker networks. To construct this graph, we selected a one percent random subsample of 85 workers who were displaced in the year 2000. The displaced workers are shown at the center of each co-worker network and edges represent the links to their former co-workers. We see that the sizes of the networks vary a lot, the largest includes about 2000 contacts and the smallest has only a single contact. Some displaced workers have networks that overlap, while other networks are isolated. This is potentially due to the random draw of displaced workers from the full population. In general, networks of two individuals who are displaced from the same firm will overlap to a certain extent. But unless their employment careers are identical during the last 5 years, the networks will only partly overlap.

Figure 4.2 is another example of the structure of the co-worker networks. The difference is that red edges represent employed links, black edges represent unemployed links while the pink edges present employed links at hiring firms. We see that the network sizes and the average employment rate in hiring firms differ. Furthermore, we can see a tendency that the more employed contacts and the more employed contacts at a hiring firms the displaced individual has, the likelier it is, that she is employed.

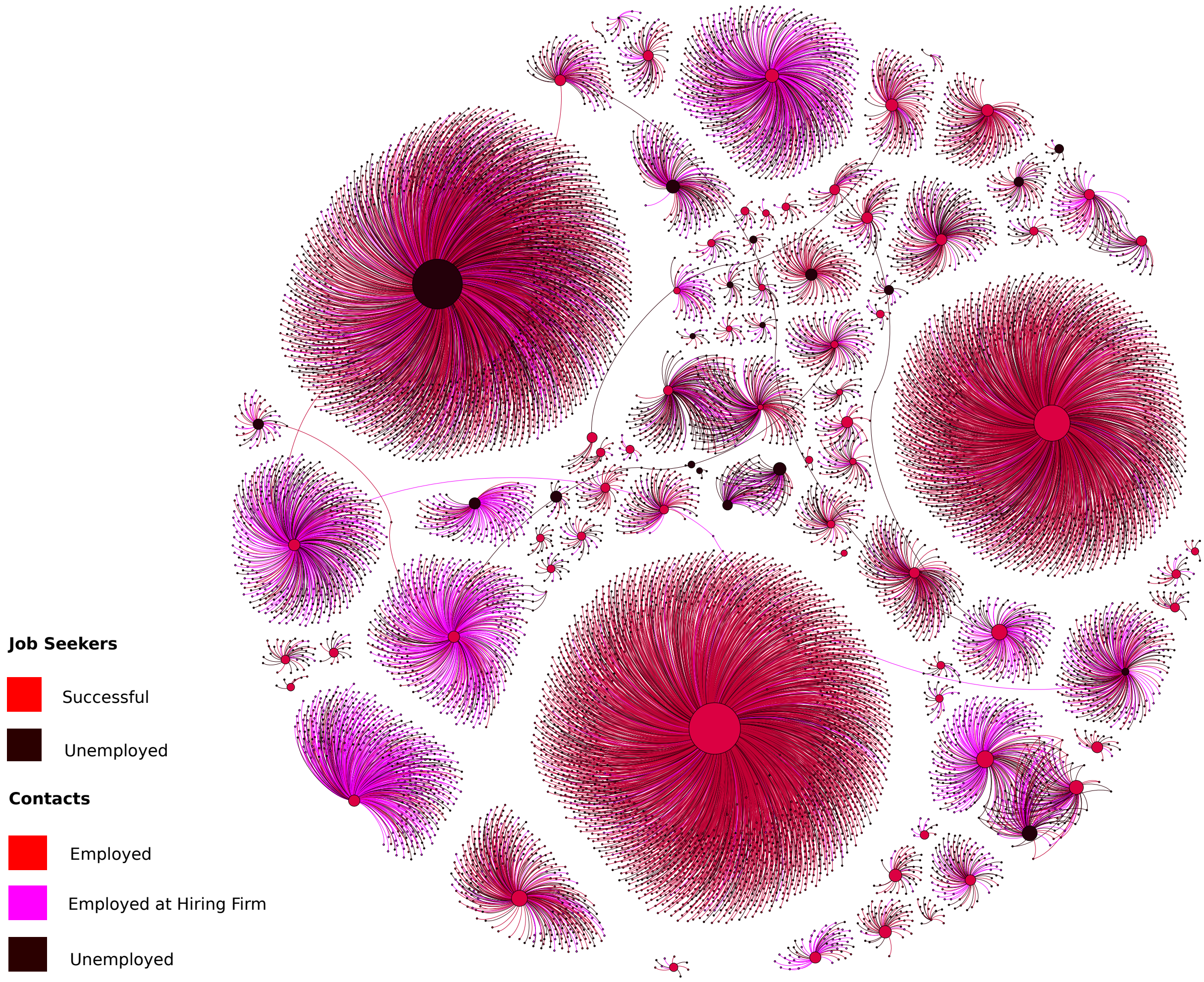
[8] Our number could be lower than Cingano and Rosolia (2012) because they only consider completed spells, and thus leave out those individuals that never get employed which by Calvo-Armengol and Jackson (2004) have a higher network unemployment rate. Thus the network employment rate of Cingano and Rosolia (2012) is automatically higher.

Figure 4.1: Job Seekers and Networks of Past Co-workers by Gender



Note: This graph is obtained from a 1% random sample of displaced workers, losing their jobs in the year 2000 due to firm closures. It illustrates the displaced workers (in the middle) and their past co-workers as connections. The blue (red) circles in the middle represent the male (female) job seekers while the blue (red) connections around them are their respective male (female) contacts in the network.

Figure 4.2: Job Seekers and Networks of Past Co-workers by Employment Status



Note: This graph is obtained from a 1% random sample of displaced workers, losing their jobs in the year 2000 due to firm closures. It illustrates the displaced workers (in the middle) and their past co-workers as connections. The red (black) circles in the middle represent the successful (still unemployed after 3 months) job seekers while the red (black) connections around them are their employed (unemployed) contacts in the network. The pink connections are the network members who are employed at a firm that is hiring at the time of the firm closure of the job seeker.

Firm Networks

At the firm level we construct networks by linking each closing firm to a network of connected firms, which is also determined by past co-workers of the displaced individuals. In particular, the set of connected firms is defined by the firms in which the past co-workers of the displaced individuals are employed at the closure date. We can think of the set of connected firms as a proxy of the local labor market which offers new job opportunities. Based on this definition our set of 27,635 closing firms is connected to 352,995 firms, which span a large fraction of the overall market.

Table 4.2 presents the main characteristics of the closing firms and their networks of connected firms. In the network analysis at the firm level we focus on closing firms with at least 2 displaced workers. On average a closing firm has former co-worker links to 175.7 connected firms, the median number of connected firms is 55. The firm network typically spans a variety of industries. On average a closing firm is linked to 38.7 connected firms in the same industry, the median is 8.8. This means that on average only about a third of the links in the firm network are among firms in the same two digit industry. In each pair of closing and connected firm there are on average two displaced individuals with links.

Figure 4.3 shows an example of a firm network. This is a random subsample of all closing firms in 2000, which includes 39 closing firms connected to an average of 105 firms (whereas the median is at 58). At the center of each network we see the closing firms and edges represent links to connected firms. Edges in red are links to firms in the same industry, while yellow edges link firms in different industries. The average share of firms in the same industry is 25%. The firm dots are color coded - the darker the color, the higher the wage quartile. The average wage quartile of the closing firm is 1.55.

Job Search Outcomes

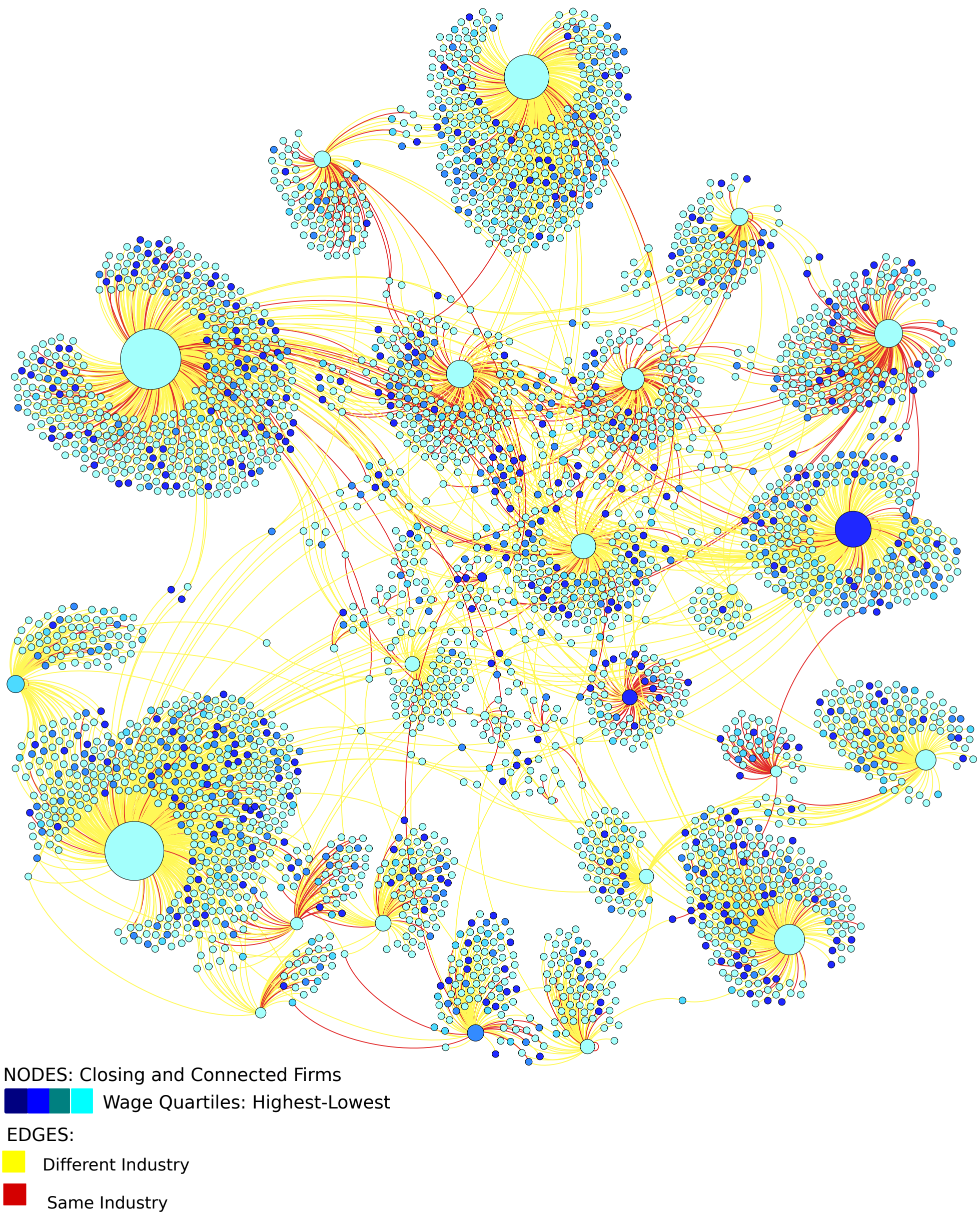
Descriptive statistics of job search outcomes are shown in Table 4.3. About 86% of the displaced workers in our sample find a new job within one year. If censored at 365 days, the average time to find a new job is 83 days but the median is only 2 days. This reflects the fact that not all displaced workers are out of employment after firm closure. About 49% transit to a new job immediately, while 33% are registering as unemployed.

Table 4.2: Firm Characteristics

	Mean	Median	Std.Dev.
Closing Firms			
Number of Displaced Workers	5.4	4	6.7
Firm Size at Maximum	23.9	13	51.4
Firm Age at Closure (years)	10.0	7.5	8.4
Wage Quartile	1.95	1.00	1.12
Vienna	0.29		0.45
Manufacturing	0.15		0.36
Construction	0.14		0.34
Sales	0.20		0.40
Tourism	0.11		0.31
Service	0.17		0.38
Firm Network Characteristics (per closing firm)			
Number of Connected Firms	175.7	55	318.4
Average Size	83.6	67.7	79.3
Average Wage Quartile	1.75	1.68	0.46
Share Same Industry	0.22	0.16	0.20
Number of Closing Firms	27,635		
Number of Connected Firms	352,995		
Per Closing - Connected Firm Pair			
Individuals with Links	1.98	1.00	4.59

Source: ASSD, own calculations.

Figure 4.3: Closing Firms and Connected Firms



Note: This graph is obtained from a 2% random sample of firms that closed in the year 2000. It illustrates the closing firms (in the middle) and the connected firms as their connections. The darker blue circles indicate higher wage firms. The yellow connections are the links between the closing firm and the connected firms that are in different industries while the red links indicate that the two firms are in the same industry.

Displaced workers who find a new job within the first year spend on average 38 days out of a job. The wages in their new jobs are about as high as the pre-displacement wages on average. If we focus on the types of firms where they find new jobs, we see that only 52% return to a firm in the same industry as the closing firm. We also check whether displaced workers return to a firm in which they were employed during the last five years and this appears to happen for 7% of displaced workers. A considerably larger share of 24% find a new job in one of the firms that are connected to the closing firm and 19% find a new job in a connected firm to which they have a personal link, i.e., where a former co-worker is employed. These numbers already indicate that referral hirings are potentially an important channel of information transmission in the co-worker networks. We will examine this more closely in our empirical analysis.

Table 4.3: Job Search Outcomes

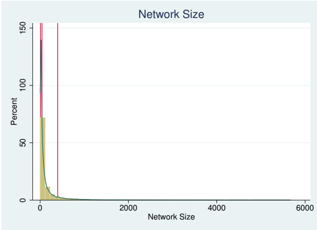
	Mean	Median	Std
All Job Seekers (N = 151,432)			
Find New Job in One Year	0.86		0.34
Time to Next Job in Days (Censored at 365)	83.19	2	131.32
New Job Immediately	0.49		0.50
Unemployed	0.33		0.47
<u>Links to Firm Network</u>			
Nb. of Connected Firms	373.8	137	655.9
Nb. of Connected Firms with Link	58.2	22	110.7
Share of Connected Firms with Link	0.40	0.24	0.37
Successful Job Seekers (N = 130,477)			
Time to Next Job Days	37.93	1	72.20
Log Wage Gain	0.009	0.015	0.301
New Job in Same Industry	0.52		0.50
New Job in Old Firm	0.07		0.25
<u>Links to Firm Network</u>			
Nb. of Connected Firms	383.0	150	636.8
Nb. of Connected Firms with Link	60.7	24	110.7
Share of Connected Firms with Link	0.39	0.24	0.36
Hired by Connected Firm	0.24		0.43
Hired by Connected Firm with Link	0.19		0.39

Source: ASSD, own calculations.

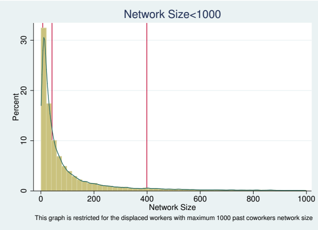
Figure 4.4 shows the distribution (histograms) of some of the most relevant network characteristics.

Figure 4.4: Distribution of Network Characteristics

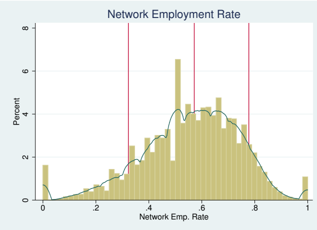
(a) Network Size



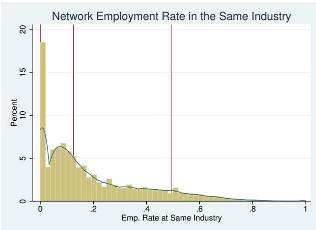
(b) Network Size Restr.



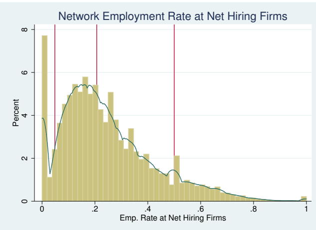
(c) Network Emp. Rate



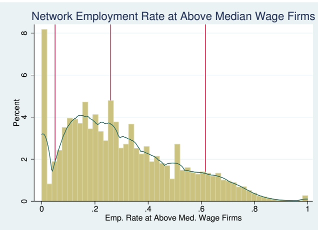
(d) Same Industry



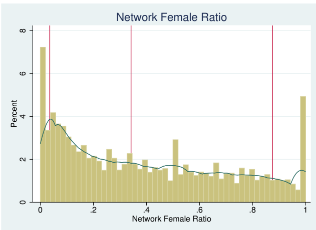
(e) Network Hiring Rate



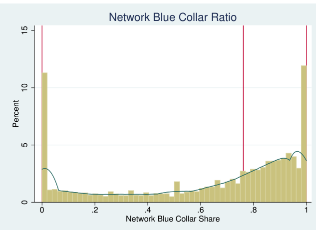
(f) Network Top 50



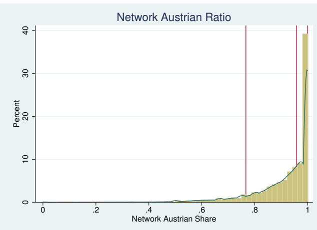
(g) Female Rate



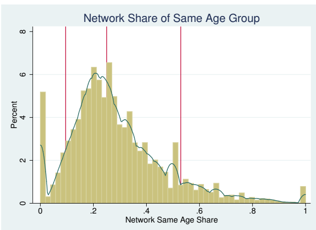
(h) Blue Collar



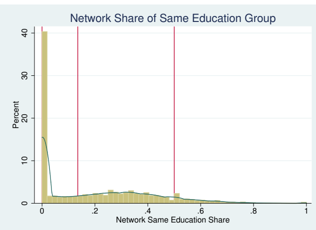
(i) Austria Collar



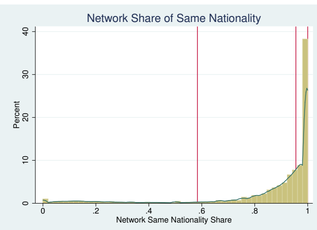
(j) Same Age



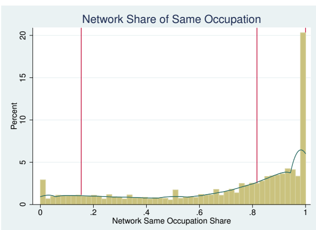
(k) Same Education



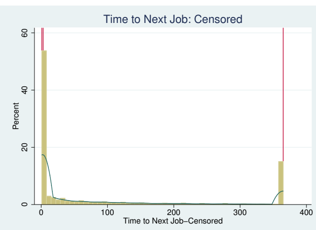
(l) Same Nationality



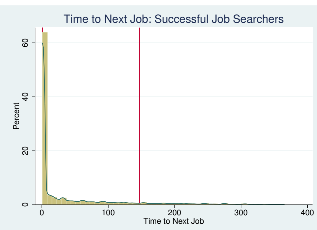
(m) Same Occupation



(n) Time to Next Job



(o) Time to Next Job Completed



Note: These graphs are obtained from our full sample of displaced workers due to firm closures between years 1980 to 2007. Except for the last graph, they illustrates the distributions of variables measuring the characteristics of network members. Starting from number of contacts (network size), share of employed contacts (also employed in same industry and in above median wage firms), blue collar contacts, same age group, nationality and occupation contacts are shown. The last graph shows the distribution of duration of job seeking after firm closure for successful job seekers.

4.3 Empirical Analysis

The empirical analysis proceeds in two parts, which exploit the worker dimension and the firm dimension of the co-worker networks. We start by investigating the effects of network characteristics on the job finding rates and wage growth after job displacement. Our main identification strategy consists of comparing workers who were displaced from the same closing firms with different networks. This will give us a first indication whether co-worker networks have an impact on job search outcomes. The second part of our analysis aims at narrowing down the channel by which information is transmitted among network members. We will exploit the firm dimension of co-worker networks and investigate the probability that a displaced worker finds a job in a firm that is connected to the closing firm. Thereby we will focus on the role of the displaced worker, the connected firm, and a potential link to a former co-worker in the connected firm on the magnitude of the social tie effect.

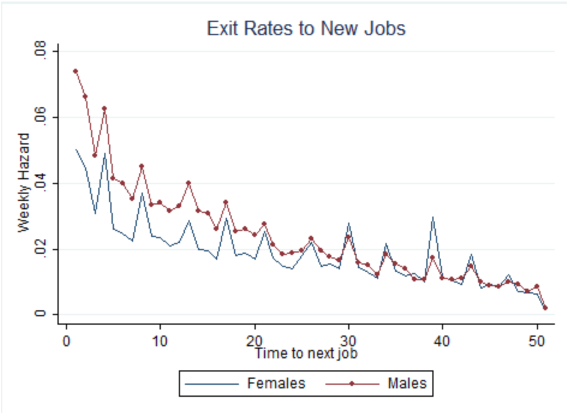
4.3.1 Worker Level Analysis

Job Finding Rates

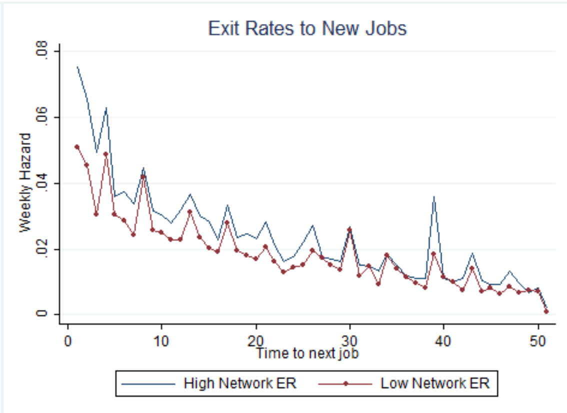
The model of information transmission in social networks by Calvo-Armengol and Jackson (2004) predicts that the share of employed network members is crucial for the job-finding success of unemployed workers. To get a first impression of this connection in our sample we present weekly hazard rates into new jobs over the first year after displacement in Figure 4.5. Panel 4.5a depicts the weekly hazards for males and females. The figure shows declining patterns in the weekly exit hazard for both groups, but males exit quicker than females. Therefore we are always controlling for gender in the following. Furthermore in Figure 4.5 we specifically focus on two subsamples of the total population: displaced workers with a share of employment of former co-workers in the top quartile of the distribution, which we denote as “high network employment rate”, and displaced workers with a share of employment of former co-workers in the bottom quartile of the distribution, denoted as “low network employment rate” (Figure 4.5b). The figure shows declining patterns in the weekly exit hazard rates for both groups. But especially during the initial weeks of job search the exit rate of individuals with a high network employment rate is clearly above the exit rate of individuals with low network employment rate. After about 5 to 6 months of job search the two lines in the graph converge and there is no difference in exit hazard rates any more. This holds whether or not the displaced individuals exit to non-referral versus referral jobs (Figures 4.5c and 4.5d).

Figure 4.5: Exit Rates to Jobs

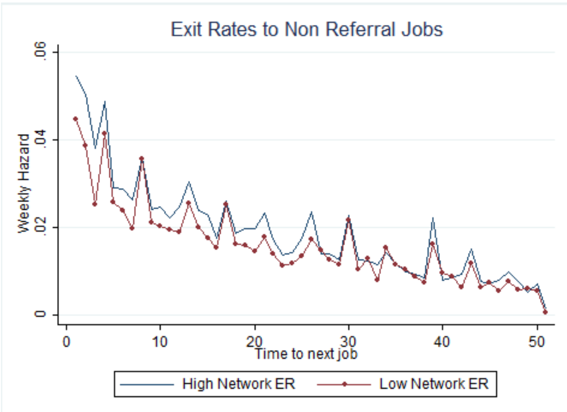
(a) By Gender



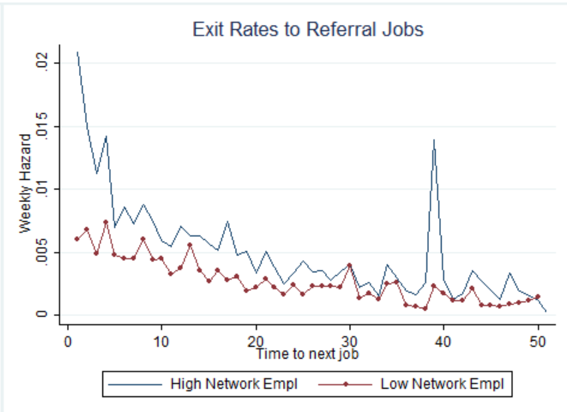
(b) By Network Employment Rate



(c) Non-Referral Network Employment Rate



(d) Referral Network Employment Rate



Note: These graphs illustrate the exit rates to new jobs for our full sample of displaced workers due to firm closures between years 1980 to 2007. Horizontal axis shows the time to next job from job loss. First graph indicates the difference between female and male job seekers while the second one shows the two subgroups of job seekers with high vs low network employment rate. The third graph shows the exit to jobs obtained without using referrals from contacts for job seekers with high and low employment rate in their networks. Last graph shows the exit to jobs obtained through referrals for job seekers with low and high network employment rate.

To see whether the graphical impression also holds after controlling for individual characteristics and closing firm effects, we estimate proportional hazard models for the risk of finding a new job in the first year after displacement. These models include unrestricted daily baseline hazards at the closing firm level, a set of individual level covariates X such as age, gender, nationality, and detailed labor market and earnings history characteristics, and a set of network characteristics NW. Specifically, we model the discrete hazard function $h(T|X_{ij}, NW_{ij})$ as the probability that individual i displaced form firm j finds a job after T days, given that she has not exited to a job up to day $T-1$, as

$$h(T|X_{ij}, NW_{ij}) = \lambda_j(T)\exp(\alpha X_{ij} + \beta NW_{ij}) \tag{4.1}$$

where the baseline function $\lambda_j(T)$ specifies the closing firm specific hazard rates when all covariates are set to zero and α and β are the vectors of coefficients to be estimated. Observations with durations longer than 365 days are treated as right censored.

Table 4.4 presents the estimation results. Columns (1) to (5) present estimates from separate regressions including different sets of network characteristics. All models control for the log network size to account for network heterogeneity in terms of the number of contacts. But the coefficient is small across all specifications and mostly insignificant. The share of co-workers who are employed at the displacement date has a large and significant impact on the job finding rate. The magnitude of the effect in Column (1) implies a one standard deviation increase in the share of employed former co-workers increases the exit rate to jobs by about 4%. This is similar in magnitude to the effect reported by Cingano and Rosolia (2012), but somewhat smaller than the IV estimates by Glitz (2013).

The remaining model specifications in Table 4.4 include variables representing the types of firms where former co-workers are employed. Column (2) controls for the share of former co-workers who are working in firms operating in the same industry as the closing firm. It turns out that former co-workers in same industry firms are about twice as effective as other employed co-workers for finding new jobs.

The next specification in Column (3) takes demand side factors, that are faced by the firms in which former co-workers are employed into account. Social contacts in expanding firms might be more helpful for displaced workers, because these firms typically have open vacancies. This idea is confirmed by the regression coefficient. The share of former co-workers employed in net hiring firms, defined as firms that were growing in the quarter of job displacement, further increases the exit rate to new jobs. Column (4) examines if this effect also holds for the share of former co-workers who are employed in firms that are growing in two consecutive quarters to make sure that the hiring of former co-workers is not the only reason for the employment growth in their firms. As the estimated coefficient remains of the same magnitude and statistically significant, we conclude that former co-workers employed in expanding firms are potentially an important source of information about vacancies in their firms.

The final specification in Column (5) examines the effect of former co-workers who are employed in firms that pay average wages above the industry specific medians. Here the coefficient is small and insignificant and we cannot see an impact on the hiring rate.

Table 4.4: Job Finding Rate: Effect of Network Characteristics

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.016	0.009	0.008	0.008	0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Network Emp. Rate	0.195	0.109	0.071	0.097	0.099
	(0.022)	(0.025)	(0.026)	(0.026)	(0.027)
Emp. Rate at Same Industry		0.134	0.136	0.133	0.131
		(0.021)	(0.021)	(0.021)	(0.021)
Emp. Rate at Net Hiring Firms			0.086		
			(0.018)		
Emp. Rate at Net Hiring Firms at t and t+1				0.074	
				(0.024)	
Emp. Rate at Above Med. Wage Firms					0.017
					(0.019)
Observations	151432	151432	151432	151432	151432

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column we add a different measure of network employment rate as indicated. We control for individual demographic and work force characteristics such as gender, age, marital status, nationality, education, occupation indicator (blue and white collar), tenure at job lost, employment days in last two years, employment days over last 5-15 years, unemployment claims in last 3-5 years, wage before job loss, number of employers within last years before job loss, average size of firms (employers) within last 5 years. All estimations also include closing firm fixed effects.

We further check the robustness of our results with respect to the model specification and to the measurement of the network characteristics. Appendix Table 4.10 presents results for the same set of model specifications as Table 4.4 that are based on linear probability models for an indicator variable equal to one if the individual is employed within 3 months after displacement. The results of this model are very similar to the results from the proportional hazard model.

Next, we estimate hazard rate models that take into account changes in the network characteristics over time. The hazard rate models in Table 4.4 are based on network characteristics measured at job displacement. For job seekers who are still out of work some time after displacement, however, the network characteristics at a later date may be more relevant. Appendix Table 4.11 therefore presents results from hazard models that allow for time varying network characteristics in the first quarters after job displacement. Qualitatively and quantitatively these results are not different from the estimations with fixed network characteristics. This is not surprising, as we have seen in Figure 4.5 that the largest differences in exit rates between individuals with high and low shares of employed former co-workers appear in the first months after displacement.

Figure 4.6 plots the employment status of jobs seekers in the quarters before and after the firm closure. The first four Panels 4.6a, 4.6b, 4.6c and 4.6d show the employment status of the displaced individuals grouped by our different network employment rate measures. They show that the individuals are not sorted by their respective network employment rates before displacement, but clearly sorted thereafter. This looks a little bit different for Panels 4.6e and 4.6f where the individuals wages are plotted. Before displacement there is already sorting according to the network employment rates (Panel 4.6e) and according to the mean wage quartile (Panel 4.6f), but the difference between the four groups is larger after displacement.

Wage Growth

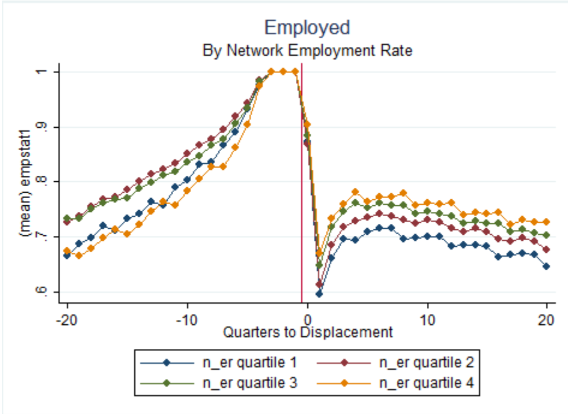
After having established the importance of network characteristics on the job finding rates, we investigate if co-worker networks also have an impact on the characteristics of the new jobs. We focus on displaced workers who successfully find a new job in the first year after firm closure and compare their pre-and post-displacement wages. Specifically, we estimate the following regression model

$$y_{ij} = X_{ij}\alpha + NW_{ij}\beta + \gamma_j + u_{ij} \tag{4.2}$$

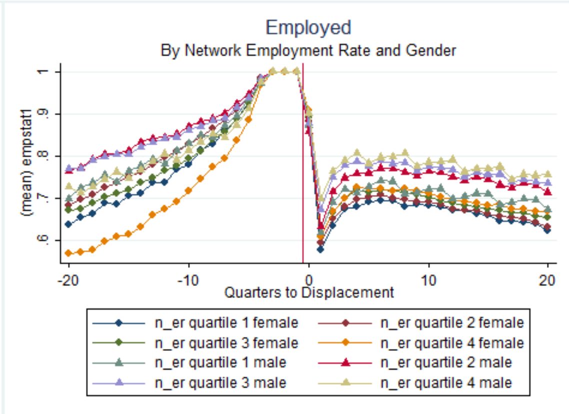
where y_{ij} denotes the log wage difference before and after displacement and γ_j controls for closing firm fixed effects. The effects of individual and network characteristics are again given by the parameters α and β. We estimate separate models for males and females, because monthly wages in the ASSD can only be constructed from annual earnings and we have no control over changes in working hours.

Figure 4.6: Employment and Wages Before and After Displacement, by Network Characteristics

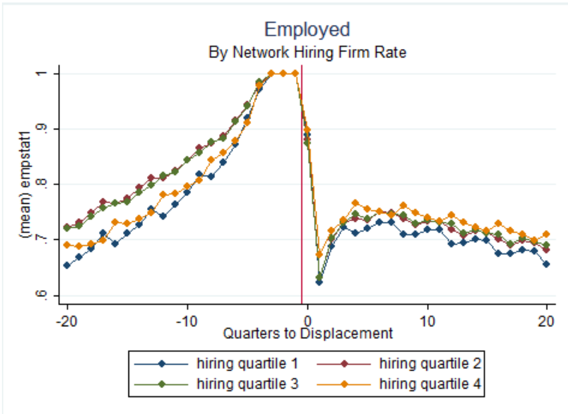
(a) Network Employment Rate



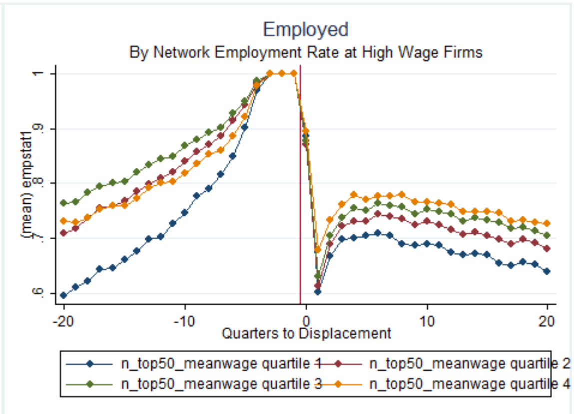
(b) Network Employment Rate by Gender



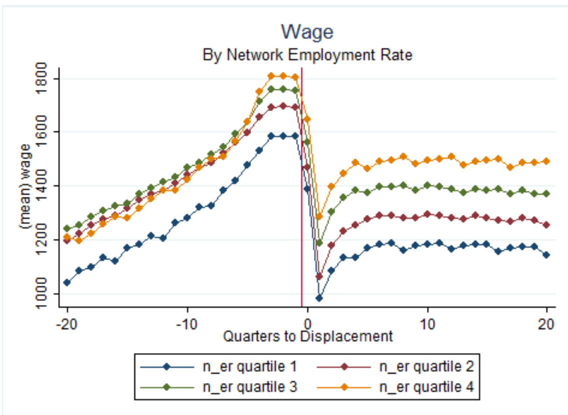
(c) Network Hiring Rate



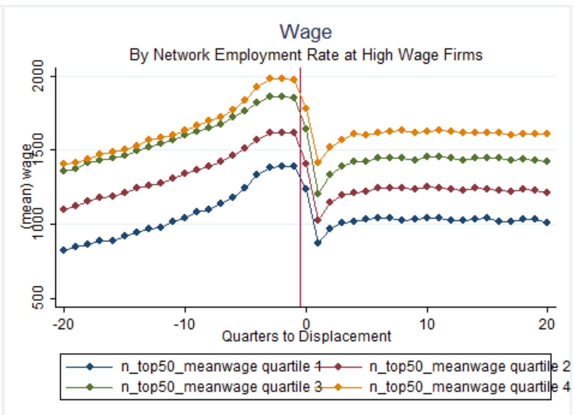
(d) Network Employment Rate at HWF



(e) Wage Network Employment Rate



(f) Wage Network Employment Rate at HWF



Note: These graphs are obtained from our full sample of displaced workers due to firm closures between years 1980 to 2007. Top two graphs illustrate the employment status of job seekers in each quarter before and after firm closure. Each line represents subgroups of job seekers in terms of different quartiles of network employment rate of job seekers. The one of the right hand side shows female and male workers separately. Two graphs in the middle also illustrate the employment status of job seekers in each quarter before and after firm closure. On the left hand side, each line represents subgroups of job seekers in terms of different quartiles of network employment rate at hiring firms and the graph on the right hand side shows job seekers from different quartiles network employment rate at high wage firms. Finally the two bottom graphs represent the wages of job seekers in each quarter before and after firm closure. The one on the left shows it for different quartiles of network employment rate while the one on the right hand side is for the subgroups of job seekers in terms of network employment rates at high wage firms.

Estimation results for men, presented in Table 4.5, show that network characteristics have only small and mostly insignificant effects on wage growth. The only significant coefficient is on the employment rate of former co-workers who work in high wage firms. Increasing this share by one standard deviation, raises the average wage gain by one percentage point. This result indicates that wage gains might be due to individuals finding jobs in higher paying firms where their former co-workers are employed.

Results for women, shown in Table 4.6, are quantitatively in line with the results for males. In contrast to men, women also seem to benefit from former co-workers who are employed in the same industry and from former co-workers employed in expanding firms. This could indicate that women who are able to return to employment more quickly also benefit in terms of reemployment wages.

Table 4.5: Wage Growth: Effect of Network Characteristics, Only Men

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Network Emp. Rate	0.025 (0.013)	0.025 (0.015)	0.024 (0.016)	0.025 (0.015)	-0.008 (0.016)
Emp. Rate at Same Industry		0.000 (0.011)	0.000 (0.011)	0.000 (0.011)	-0.008 (0.011)
Emp. Rate at Net Hiring Firms			0.003 (0.010)		
Emp. Rate at Net Hiring Firms at t and t+1				0.002 (0.013)	
Emp. Rate at Above Med. Wage Firms					0.055 (0.011)
Observations	78110	78110	78110	78110	78110

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. Estimation sample includes only male displaced workers displaced workers due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. In each column, we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as individual demographic and work force characteristics.

Heterogeneity of Job Finding Rates

Next, we examine whether the network effects are heterogeneous for different groups of displaced workers. In addition, we investigate whether former co-workers with similar characteristics are more profitable for the job finding rate. We estimate hazard rate models similar to Equation 4.1 for several sub-populations, with controls for log network size and the share of employed network members. In particular, we divide network members into four distinct categories: employed

Table 4.6: Wage Growth: Effect of Network Characteristics, Only Women

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.009	0.006	0.006	0.006	0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Network Emp. Rate	0.016	-0.008	-0.024	-0.012	-0.028
	(0.017)	(0.020)	(0.021)	(0.020)	(0.021)
Emp. Rate at Same Industry		0.040	0.040	0.040	0.034
		(0.017)	(0.017)	(0.017)	(0.018)
Emp. Rate at Net Hiring Firms			0.037		
			(0.015)		
Emp. Rate at Net Hiring Firms at t and t+1				0.021	
				(0.020)	
Emp. Rate at Above Med. Wage Firms					0.042
					(0.015)
Observations	52367	52367	52367	52367	52367

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. Estimation sample includes only female displaced workers displaced workers due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. In each column, we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as individual demographic and work force characteristics.

network members of the same population group, employed network members of the opposite population group, not employed network members of the same population group, and not employed network members of the opposite population group who are the reference group.

Estimation results by gender, occupation, and nationality are shown in Table 4.7. To facilitate the comparison of the estimated effects across groups and across covariates, we standardize the coefficients such that they correspond to the effects of a one standard deviation increase of the independent variable. The first column reports the result for female displaced workers. Females benefit from employed former co-workers of either gender, an increase by one standard deviation increases the job finding rate by about 5 - 6%. Even non-employed female network members are more important for job finding success of women than non-employed male network members.

Males, shown in Column (2), in comparison, mostly benefit from employed male former co-workers, while employed female network members are slightly less important. Non-employed contacts do not have any effect on the job finding rate of male displaced workers.

If we compare network effects by workers types, in Columns (3) and (4), we note that for white collar workers the impact of former co-workers on the job finding rates are much stronger than on blue collar workers. An increase of the share of former co-workers by one standard deviation corresponds to a shift in the hazard rate by about 8 - 9% for white collar workers, but only for an increase by about 2% for blue collar workers. Interestingly, white collar workers benefit from all types of employed former co-workers, white and blue collar. Non employed blue collar network members do not seem to be profitable for either type of job seeker. Cutting the sample by nationality reveals that job information seems to be mostly traded among Austrian workers. Job finding rates of displaced workers of Austrian nationality are more than twice as highly correlated to the share of employed Austrian former co-workers than to employed former co-workers of different nationalities. For displaced workers with non-Austrian nationality, we do not find any significant network effects.

Table 4.7: Job Finding: Effect of Similar Charcteristics

	Female	Male	Blue Collar	White Collar	Austrian	Non-Austrian
Network Size	0.027	0.026	-0.002	0.052	0.033	-0.034
	(0.009)	(0.008)	(0.008)	(0.008)	(0.006)	(0.021)
Employed Same Group	0.047	0.048	0.02	0.08	0.059	0.005
	(0.009)	(0.009)	(0.010)	(0.010)	(0.017)	(0.016)
Employed Opposite Group	0.055	0.033	0.014	0.087	0.023	0.003
	(0.012)	(0.009)	(0.011)	(0.013)	(0.008)	(0.021)
Unemployed Same Group	0.031	0.004	-0.009	0.04	0.024	-0.01
	(0.011)	(0.009)	(0.011)	(0.010)	(0.017)	(0.018)
Observations	62,766	88,666	80,604	70,828	138,010	13,422

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column the estimation sample is a sub-group of displaced workers such as Female, Male, Blue Collar, White Collar, Austrian, and Non-Austrian. In each estimation, variables of interest are employment and unemployment rate of same or opposite subgroup in the network. We standardized these variables such that the coefficient corresponds to the effect of a one standard deviation increase in the independent variable. All estimations include closing firm FE as well as individual demographics and work force characteristics.

Table 4.8 reports network effects on the job finding rates by age groups. Here the results also indicate some heterogeneity. Overall, the workers in the oldest and in the youngest age groups seem to be most affected by the employment rate among former co-workers, while prime age workers appear to be less reliant on their networks for finding a new job.

4.3.2 Firm Level Analysis

The results so far confirm that network characteristics are strongly related to job search outcomes of displaced workers. In line with Cingano and Rosolia (2012) and Glitz (2013) we find that the share of employed former co-workers has a positive impact on the job finding rates. But which is the mechanism driving these results? Our results also provide some indication that job referrals might be an important channel. We find that the type of firm where former co-workers are employed matters. Especially former co-workers in expanding firms have a positive impact on

Table 4.8: Job Finding: Effect of Similar Age Groups

	Below 29	29 to 36	36 to 44	Above 44
Network Size	0.078	-0.001	0.019	-0.009
	(0.013)	(0.014)	(0.013)	(0.014)
Employed Same Group	0.06	0.021	0.013	0.054
	(0.010)	(0.009)	(0.009)	(0.011)
Employed Age < 30		0.022	0.048	0.084
		(0.011)	(0.012)	(0.015)
Employed Age $30 - 35$	0.002		0.019	0.036
	(0.008)		(0.009)	(0.012)
Employed Age $36 - 44$	0.02	0.012		0.041
	(0.009)	(0.009)		(0.011)
Employed Age > 44	0.022	0.013	0.024	
	(0.009)	(0.010)	(0.010)	
Unemployed Same Group	0.014	0.001	0.006	0.042
	(0.012)	(0.010)	(0.011)	(0.015)
Observations	36,030	35,244	38,404	41,754

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column the estimation sample is a sub-group of displaced workers in terms of age groups such as below 29, between 30 and 36, between 36 and 44, and above 44. In each estimation, variables of interest are employment and unemployment rate of same or opposite subgroup in the network. We standardized these variables such that the coefficient corresponds to the effect of a one standard deviation increase in the independent variable. All estimations include closing firm FE as well as individual demographics and work force characteristics.

job finding rates. In addition we find wage gains in the new job for displaced workers whose former co-workers are employed in high wage firms. Arguably the firm type should only matter for search outcomes if network information leads to jobs in these expanding or high wage firms.

The next part of the analysis examines the importance of the referral channel further. We exploit the firm dimension of the co-worker network and ask the question: what is the contribution of a former co-worker contact k employed at a connected firm l on the probability that the displaced individual i gets hired? To avoid spurious correlation in unobservable characteristics of the worker and the firm, i.e., that firm l is generally more likely to hire workers of i's type we control for fixed effects at the pair level of closing and connected firms. The counterfactual analysis thus compares two workers from the same layoff firm j where one of them holds a link with a former co-worker employed in connected firm l and the other one does not.

We thus specify our regression model as a linear probability model

$$P_{i,j,l} = \beta_{jl} + \gamma L_{il} + \epsilon_{il} \tag{4.3}$$

where $P_{i,j,l}$ denotes the probability that individual i displaced from firm j is hired by connected firm l and L_{il} is an indicator equal to one if the individual holds a link to a former co-worker employed at l. Thus γ measures the network effect.

Estimating this model requires a large dataset which has a dimension determined by the number of displaced workers times closing firms times connected firms, which makes Equation (4.3) intractable. To simplify the estimation, we apply a fixed effects transformation suggested by Kramarz and Thesmar (2013) and applied by Kramarz and Nordstrom Skans (2013). In particular, we collapse Equation (4.3) at the closing - connected firm level and consider the share of linked individuals displaced from firm closing firm j, who are hired by connected firm l, $R_{j,l}^{Link}$ given by:

$$R_{j,l}^{Link} = \frac{\sum_i P_{ijl} * L_{il}}{\sum_i L_{il}} = \beta_{jl} + \gamma + u_{il}^{Link}$$

and the share of non-linked individuals displaced from closing firm j, who are hired by connected firm l, $R_{j,l}^{noLink}$ given by

$$R_{j,l}^{noLink} = \frac{\sum_i P_{ijl} * (1 - L_{il})}{\sum_i (1 - L_{il})} = \beta_{jl} + u_{il}^{noLink}$$

The difference between these two determines the coefficient of interest γ as

$$G_{j,l} = R_{j,l}^{Link} - R_{j,l}^{noLink} = \gamma + u_{il} \tag{4.4}$$

Estimation results are shown in Table 4.9. The first row presents the estimate of γ and its components for the full sample. The parameter on the link dummy is estimated with high precision. To interpret it's magnitude we compare the share of linked workers who get hired with the share of non-linked workers who get hired. The ratio between those two is 3.4, which means that workers with link face a more than three times higher probability to find a job in the connected firm as similar workers from the same closing firm without a link.

To see whether the result for the overall sample is driven by certain subgroups, we repeat the estimation for various subsamples in the remaining columns of Table 4.9. Although the coefficient estimate of the link effect varies across groups, for example γ is higher in pairs of closing - connected firms in the same industry, the ratio between the share hired with link and the share hired without link is roughly stable. For example, both linked and non-linked individuals have a higher probability of being hired in a connected firm in the same industry. We also confirm that the link effect does not change over time, by region, and for larger closing firms which probably also have a higher variation of links across connected firms.

Table 4.9: Firm Level Analysis

	All	Vienna	Same industry	Year > 1995	Layoffs > 10
γ	0.00062	0.00047	0.00125	0.00047	0.00041
	(0.00001)	(0.00002)	(0.00005)	(0.00002)	(0.00002)
t-stat	45.66	24.19	24.18	30.79	23.03
$R_{j,l}^{Link}$	0.00088	0.00067	0.00204	0.00070	0.00058
	(0.00001)	(0.00002)	(0.00005)	(0.00002)	(0.00002)
$R_{j,l}^{noLink}$	0.00025	0.00020	0.00079	0.00023	0.00017
	(0.00001)	(0.00001)	(0.00003)	(0.00001)	(0.00001)
Ratio	3.44	3.40	2.58	3.06	3.37
N	4,197,692	1,569,564	625,944	2,592,747	1,376,913

Source: ASSD, own calculations.
Note: Observation pairs of the analysis is layoff firm and connected firm. Displaced workers with a link to connected firm are 3.44 times as likely to be hired as co-displaced workers without a link from the same layoff firm.

4.4 Conclusion

A growing theoretical and empirical literature on the relevance of social networks in the labor market provides various channels through which networks can affect the labor market. So far, the empirical studies testing the theoretical implications have remained relatively scarce, with very little consensus on the various channels.

In order to understand how displaced workers benefit from their social contacts to find a job, we define the social networks as the group of past co-workers with whom they worked together (during the past five years) at the same firm. We use large administrative data providing the entire work histories of the universe of private sector workers in Austria.

Our contribution to the empirical analysis of social networks on job search outcomes is two-fold. First, we provide evidence of an effect of the social network at the job seeker level, where we show that the higher the share of employed past co-workers the higher is the job-finding rate of the displaced worker. Furthermore, past co-workers employed in the same industry and in firms that are hiring at the displacement date are particularly helpful. We also provide evidence on the heterogeneity of network effects where past co-workers with similar characteristics are important for some groups based on gender, age groups and occupation. Second, we bring the analysis to the firm level, where we define the firm networks based on the links between the corresponding workers. We find that 25% of the displaced workers find a new job in a connected firm and that the displaced workers with a link to the connected firm are three times as likely to be hired as co-displaced workers from the same layoff firm without a link to the connected firm.

4.A Networks Appendix

4.A.1 Reemployment Probability

In this section, we present the results of the linear probability model of employment within 3 months after displacement. We consider the whole sample of displaced workers and analyze whether the network employment rate has an impact on the probability of their re-employment. Table 4.10 shows that the network employment rate has a significant positive effect on the probability of re-employment. We control for the individual characteristics of the displaced worker as well as her employment history. All estimations include closing firm fixed effects. Table 4.10 presents evidence of a significant impact of the network employment rate on the re-employment probability after 3 months. This impact is mostly driven by network members that are employed in the same industry (Column 2) and hiring firms (Column 3 and 4) while the share of network members employed in above median wage firms (Column 5) do not have a significant impact.

Table 4.10: Probability of Reemployment: Effect of Network Characteristics

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.005	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Network Emp. Rate	0.071	0.020	0.003	0.016	-0.002
	(0.012)	(0.014)	(0.014)	(0.014)	(0.015)
Emp. Rate at Same Industry		0.080	0.081	0.080	0.079
		(0.011)	(0.011)	(0.011)	(0.011)
Emp. Rate at Net Hiring Firms			0.039		0.039
			(0.010)		(0.010)
Emp. Rate at Net Hiring Firms at t and t+1				0.026	
				(0.013)	
Emp. Rate at Above Med. Wage Firms					0.009
					(0.010)
Observations	151432	151432	151432	151432	151432

Source: ASSD, own calculations.
Note: Standard errors in parentheses. In all columns, we present results from a linear probability model where the dependent variable is a binary variable indicating reemployment within 3 months after job loss. In each column we add a different measure of network employment rate as indicated. All estimations include the same covariates as in Table 4.4 and closing firm fixed effects.

4.A.2 Robustness Checks

Table 4.11 reports results from the Cox model where we allow the network employment characteristics to change across quarters while workers search for jobs. This is a robustness check, which takes into account the time varying characteristics of the network.

Table 4.11: Job Finding Rate: Effect of Time Varying Network Characteristics

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.018	0.009	0.009	0.009	0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Network Emp. Rate	0.171	0.078	0.033	0.065	0.019
	(0.022)	(0.025)	(0.026)	(0.025)	(0.028)
Emp. Rate at Same Industry		0.146	0.148	0.145	0.144
		(0.021)	(0.021)	(0.021)	(0.021)
Emp. Rate at Net Hiring Firms			0.101		0.100
			(0.018)		(0.018)
Emp. Rate at Net Hiring Firms at t and t+1				0.078	
				(0.024)	
Emp. Rate at Above Med. Wage Firms					0.027
					(0.019)
Observations	247926	247926	247926	247926	247926

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment where we allow network employment rates vary across quarters. In second and third columns, we add network employment rate in same industry and network employment rate at hiring firms and both variables as well as network employment rate vary across quarters. All estimations include the same covariates as in Table 4.4 and closing firm fixed effects.

Another robustness check that we conduct, is to exclude some sectors such as construction, agriculture, gastronomy and tourism. Excluding these sectors we run the same analysis for the exit hazard from unemployment. Table 4.12 shows results for the sample excluding displaced workers coming from these sectors.

Table 4.12: Job Finding Rate: Excluding Agriculture, Tourism, and Construction

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.022	0.014	0.014	0.014	0.014
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Network Emp. Rate	0.221	0.135	0.096	0.121	0.126
	(0.024)	(0.028)	(0.030)	(0.029)	(0.031)
Emp. Rate at Same Industry		0.132	0.134	0.131	0.130
		(0.023)	(0.023)	(0.023)	(0.023)
Emp. Rate at Net Hiring Firms			0.090		
			(0.020)		
Emp. Rate at Net Hiring Firms at t and t+1				0.092	
				(0.027)	
Emp. Rate at Above Med. Wage Firms					0.016
					(0.021)
Observations	116197	116197	116197	116197	116197

Source: ASSD, own calculations.
Note: Standard errors in parentheses. All columns report robustness results from standard Cox Model for exiting unemployment. Estimation sample includes displaced workers who lost their jobs at closing firms excluding construction and tourism sectors. In each column we add a different measure of network employment rate as indicated. All estimations include the same covariates as in Table 4.4 and closing firm fixed effects.

Chapter 5

Selective Firing and Lemons?

5.1 Introduction

"To hire somebody is frequently to purchase a lottery" - Spence (1973)

Among others, Spence (1973) recognized that information asymmetries, which may even resemble a lottery, are crucial for the labor market and its employment dynamics. The focus of the current work is on what information firms infer from the three common types of displacement: individual layoffs, individuals displaced due to a closure, and individuals displaced due to a mass layoff.[1] I thereby bring together two strands of the literature, namely the literature on signaling and sorting. The contribution to the literature is threefold: first I test whether the individual layoffs are the least productive, second I investigate whether individual layoffs are perceived as "lemons" (with a specific focus on the high ability) and third I raise the question whether the "lemon" exists in the resulting matching pattern.

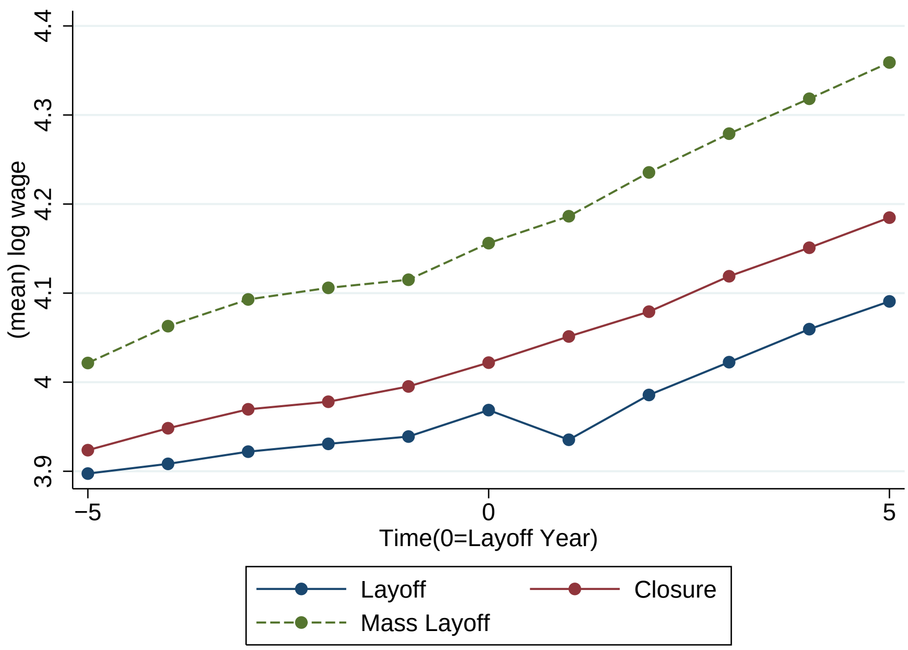
The signaling literature suggests that an agent/individual conveys information about her type (in our case ability) to another principal/party (the firm in our case). Akerlof (1970), Spence (1973) and Greenwald (1986) are examples of papers, which have considerably formed our knowledge about signaling models in the context of wages, mobility and education. As individual ability is incompletely observed by a firm, I try to disentangle if either the firms infer information from the layoff type or if the individual grasps the opportunity to find a better matching firm. The idea of a better match follows the sorting idea (assortative matching). We talk about assortative matching if more matches of certain workers and firms are observed than random matches.

[1] A person that gets fired individually and not due to a mass layoff or a firm closure is part of the individual layoff group.

Becker (1973) is a prominent example of the matching model for the marriage market.

Other than the prominent "lemon" example in Akerlof (1970) for the used car market, Gibbons and Katz (1991) (in the following referred to as GK) have shaped our expectations of what we should find when comparing individual layoffs with closures, as the individual layoffs always experience a wage penalty, after being laid off. This is also the case for Austria as we can see in Figure 5.1, which plots the wage profiles for the layoff types five years before and five years after displacement, where year 0 is the displacement year. Looking at the individual layoffs wage profile, a clear kink labeled "lemon" by GK at year 1 is visible. Already in the second year of re-employment, individuals have caught up from this drop in re-employment wages. Nevertheless, on average individuals suffering from an individual layoff never seem to catch up with the individuals displaced due to a plant closure.

Figure 5.1: Mean Wages Re-employed Individuals



GK set up an asymmetric information model and test it empirically. The first assumption that GK make, in order to derive their theoretical prediction, is that firms have leeway when determining whom to layoff. Thus, an individual layoff may be stigmatized compared to an individual losing her job due to a firm closure where no such stigma is attached. The first contribution of this work is to test whether the least able are laid off individually. In order to perform this test, I follow the seminal work of Abowd et al. (1999) (in the following referred to as AKM) where I estimate a simple wage regression with a person and a firm fixed effect. The person and firm fixed effects are used as a heterogeneity measure.[2] This measure allows me to show that the individuals suffering from a closure are more heterogeneous in terms of their productivity than the individuals laid off due to a mass layoff, which in turn are more heterogeneous than those individually laid off. This finding supports the assumption frequently made in the literature.[3]

The second contribution of this chapter is the replication of GK. As equilibrium outcome of GK asymmetric information model, re-employment wages of the individually laid off are smaller than those of the closure individuals. This leads to the main conclusion that individual layoffs are perceived as "lemons". Replicating GK, I find that a stigma is attached to being individually laid off for the case of Austria. This significantly negative effect of being fired is robust to the inclusion of a control for firm size and other controls such as region and industry.[4]

Combining Krashinsky (2002), who claims that individual layoffs have more to lose, and Hu and Taber (2005), who split their sample by race and gender and thereby put more weight on the heterogeneity of the individuals, I take the GK formulation a step further and add an analysis for high productivity individuals.[5] The analysis of the high ability individuals shows that indeed they have the most to lose, since they are not able to overcome the stigma of being individually laid off and still pay a wage penalty compared to the closure group. This result supports GK signaling argument that the individual layoffs are perceived as "lemons".

Furthermore, I raise the question whether individual layoffs have a chance of ending up at a high wage firm (HWF) (measured by the firm fixed effect from the AKM model). My findings are reconcilable with Gibbons et al. (2005), who show that unobserved ability does not explain

[2] Following Card et al. (2013b) closely, I apply AKM to the Austrian Social Security Registers and I am able to show that the identification restrictions are met.

[3] Since the seminal work of AKM, there are only a few papers which deal with inference on the fixed effects, Serafinelli (2012) and Card et al. (2013a) are two examples of papers that split the firm fixed effects into e.g., quintiles and make inference based on these.

[4] Other papers which replicate GK are for example: Grund (1999), Doiron (1995), Stevens (1997). Grund (1999) uses German Data, but does not find any evidence in favor of signaling. Doiron (1995) replicates GK for Canada. Stevens (1997) tries to replicate the findings for the US using the PSID, and does find smaller wage changes for the closing types, but much of it can be explained by the wage losses in the year prior to the actual closure event. Song (2007) and Borowitz (2010) on the other hand claim that it is all about recall bias when using the Displaced Worker Supplement to the CPS (which is the Data used by GK), while Nakamura (2008) extends the finding over the business cycle.

[5] Krashinsky (2002) explores an alternative hypothesis, claiming that individual layoffs have more to lose, since they get laid off by larger firms. Introducing controls for firm size, removes the difference between individual layoffs and closure types for his case. Hu and Taber (2005) find the "lemons" effect for some groups but a reversed result for others, pointing towards statistical discrimination.

intra-industry wage differentials and find that high-wage sectors employ high skill workers and thus also offer higher returns to workers' skills. I find that compared to individuals suffering from a closure, individual layoffs are less likely to end up at a HWF, while an individual layoff of high ability is more likely to end up at a HWF. This result may point toward exploitation, since HWF still hire individual layoffs of high ability, but they offer them a lower wage.

The main concern with the empirical finding of GK, is that it can be reconciled with a sorting model. Replicating their argument against sorting, I am not able to reject the matching model. Therefore, the third contribution of this chapter, is to see whether there is matching before the displacement and how and if it changes thereafter. There have been numerous suggestions on how to measure matching, the AKM model allows us to analyze the correlation between the worker and the firm fixed effect, as Abowd et al. (2004) have done for the US (finding a zero correlation) and for France (finding a negative correlation). These results reject the assortative matching model of Becker (1973).[6]

The consistently close to zero or even negative correlation between the person and firm fixed effects is consistent with a model known as the "piece rate model"; a model based on Burdett (1978) and extended with worker heterogeneity. Lopes de Melo (2013) applies AKM to Brazilian data and rejects the "piece rate model", then develops a measure of sorting based on Shimer and Smith (2000) which extends the search model of Becker (1973) by introducing search frictions. In these two models, complementarities in production are the main force that drive assortative matching.[7] As noted in Eeckhout and Kircher (2011) as well, the model of Shimer and Smith (2000) allows to infer the strength of the sorting, since high skill workers work for high productivity firms in case of positive assortative matching (or low productivity firms in case of negative assortative matching) as a consequence of this, they have high skilled co-workers. Thus the correlation between the person effect and the average over the co-worker person effect is a promising way to measure the intensity of sorting in the economy.

To measure sorting, this chapter uses three distinct measures; the firm fixed effect, the correlation between the person and the firm fixed effect, and the correlation between the person effect and

[6]Haskel et al. (2005) find that more productive firms hire more productive workers applying AKM to the UK (positive correlation) and Irzano et al. (2008) applying AKM to Italy find that the firm's productivity is positively related to skill dispersion within the occupational status groups and negatively to the skill dispersion between groups.

[7]Other papers related to this strand of literature are e.g., Bagger and Lentz (2008), Lise et al. (2012). I refer the reader to Lentz and Mortensen (2010) for a good overview of the labor market models with worker and firm heterogeneity.

the average of the co-worker person effect. I compare the amount of matching before displacement with the amount of matching thereafter. In a world where the signal contains no information, I expect the “lemon” to be invisible in the resulting matching pattern. This means that the matching measure should change in a similar way for the different layoff groups. If the signal distorts the resulting matching pattern, I should observe a difference between the change in matching before and after displacement. Applying the sorting measures to the ASSD, I find that the matching changes differently for the different layoff groups. This leads to the tentative conclusion, that both sorting and signaling play a role. Assortative matching plays a role, as the sorting measures are always different from zero, while signaling plays a role, because the effects change differently for the different groups.

The remainder of this chapter is structured as follows. In Section 5.2, the underlying theory and empirical framework are discussed. Section 5.2.1 discusses the GK model, while Section 5.2.2 gives a short overview of the AKM model. Section 5.2.3 talks about the possible sorting mechanism. Section 5.3 presents the linked employer-employee data of the Austrian Social Security Registers, and discusses the displacement sample. Section 5.4 presents the results, where Section 5.4.1 provides the reader with the results on the heterogeneity while Section 5.4.2 discusses the signaling versus sorting evidence. Section 5.5 concludes.

5.2 Theoretical and Empirical Framework

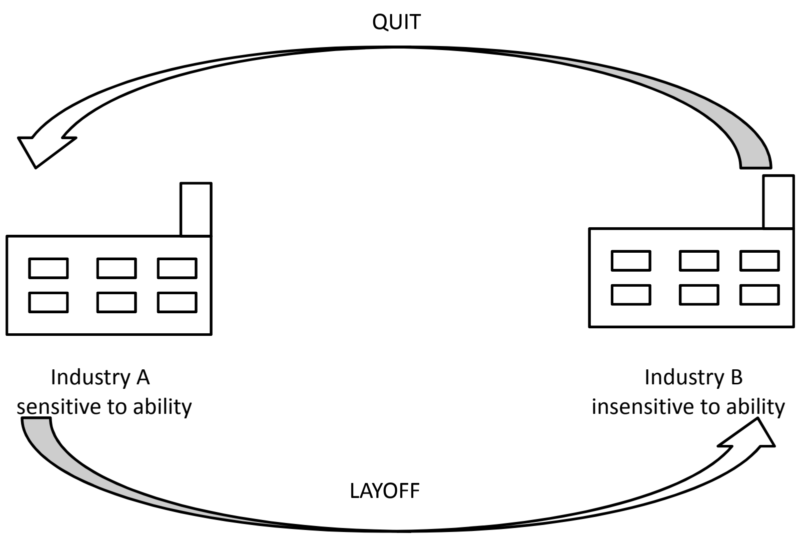
As discussed above, the analysis for signaling follows Gibbons and Katz (1991), while part of the sorting is based on Lopes de Melo (2013). Section 5.2.1, describes the signaling according to GK and the possible sorting explanation of their findings. Section 5.2.2 describes the heterogeneity measures, allowing to differentiate between a high and low ability individual and a high and low wage paying firm. Section 5.2.3 discusses the different measures of sorting and what could be a possible mechanism to disentangle signaling and sorting.

5.2.1 Signaling according to Gibbons and Katz (1991)

GK provide a theoretical analysis of an asymmetric information model for layoffs. The model describes the labor market as an uncertain environment with informational frictions, where it is assumed that the firm has discretion over whom to layoff. Then the firm’s desire to retain a worker, signals that the worker is of high ability, and therefore the market will bid up the wage of the retained worker. However, this effect will represent an adverse effect for individual layoffs, and therefore they will receive lower re-employment wages. The equilibrium outcome of their model for re-employment wages is: $\omega_{\text{closure}} > \omega_{\text{individual layoff}}$. GK conjecture and empirically show, using the displaced worker supplement to the CPS, that individual layoffs compared to displacements due to plant closures exert a negative signal for the workers ability, by earning lower re-employment wages.

The problem with this finding, also mentioned in their paper, is that sorting could be another consistent explanation. The sorting consistent example that they give, see also Figure 5.2, is that if there is an industry A which is sensitive to ability, and at the beginning of the period all the seemingly high ability individuals work in A. While industry B is insensitive to ability, and all the seemingly low ability individuals work in B. Then over time endogenous mobility will improve the quality of the match. If moves from A to B are labeled as a layoff, and those from B to A as a quit, it generates the exact same prediction as the signaling model.

Figure 5.2: Possible Sorting Mechanism in the GK model



GK test the matching model by including an industry switch dummy, and an interaction between the industry switch dummy and the layoff dummy. They interpret the drop of the significance on the layoff dummy as evidence that sorting (matching) is not the dominant mechanism.

As GK asymmetric information model is used as the framework for the analysis, I will replicate their findings using (and expanding) their empirical specification;

$$\underbrace{\Delta\omega}_{\omega_{\text{post}}-\omega_{\text{pre}}} = \delta_1 1(\text{Layoff}) + \beta X \tag{5.1}$$

where the prediction that $\delta_1 < 0$ is testable, $1()$ represents the indicator function and X are other control variables.[8] To replicate GK findings on the symmetric information story, the following empirical specification will be estimated:

$$\omega_{\text{post}} = \delta_1 1(\text{Layoff}) + \gamma_1 1(\text{Switch Industry}) + \gamma_2 1(\text{Switch Industry} * \text{Layoff}) + \beta X \tag{5.2}$$

Laid off individuals switching industry should receive especially low re-employment wages; $\gamma_2 < 0$ for the finding to be in line with a matching model. GK find that: $\gamma_2 > 0$ and small in magnitude and therefore exclude matching as a possible explanation. To take GK a step further, I first include mass layoffs when estimating Equation (5.1) resulting in the following specification;

$$\Delta\omega = \delta_1 1(\text{Layoff}) + \delta_2 1(\text{Mass Layoff}) + \beta X \tag{5.3}$$

and then take it even a step further and include an indication of whether or not the individual is a high ability type individual (HA).

$$\Delta\omega = \delta_1 1(\text{Layoff}) + \delta_2 1(\text{ML}) + \delta_3 1(\text{HA}) + \delta_4 1(\text{HA} * \text{Layoff}) + \delta_5 1(\text{HA} * \text{ML}) + \beta X \tag{5.4}$$

With this specification, the question whether a high ability individual is able to overcome his layoff stigma may be answered by testing; $\delta_1 + \delta_3 + \delta_4 \geq 0$. A high ability individual has potentially the most to lose, and therefore this specification allows to test whether there is a stigma attached to being laid off.

In this context, the question may be raised whether a laid off individual (L) even has a chance of being hired at a high wage firm (HWF). To do so I estimate a logit model of the following form:

$$Pr((HWF) = 1) = \lambda_1 1(\text{L}) + \lambda_2 1(\text{ML}) + \lambda_3 1(\text{HA}) + \lambda_4 1(\text{HA} * \text{L}) + \lambda_5 1(\text{HA} * \text{ML}) + \beta X + \epsilon \tag{5.5}$$

[8] In the empirical section I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since labor force participation (LFP), employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

which answers, whether an individual layoff is more likely to end up at a HWF than a closure, and whether an individual layoff, which is also of high ability is more likely to end up at a HWF.

5.2.2 Measure of Productivity and Sorting

In order to measure a workers productivity, which is unobserved to an econometrician and which is partly unobserved to the firm, I will use the worker fixed effect from an Abowd et al. (1999) type wage decomposition. Productivity may only be partly observed to the firm since for example education is observable and easy to clearly communicate to a hiring firm. Furthermore in order to know whether a firm is paying higher wages, the firm fixed effect of the Abowd et al. (1999) wage decomposition is used;

$$\begin{aligned} \omega_{it} &= \underbrace{\alpha_i + \Psi_{J(i,t)}}_{\text{Fixed Effects}} + x_{it}^{'}\beta + \underbrace{\eta_{iJ(i,t)} + \varsigma_{it} + \epsilon_{it}}_{\text{Random Effects}} \\ &= \alpha_i + \Psi_{J(i,t)} + x_{it}^{'}\beta + r_{it} \end{aligned} \tag{5.6}$$

where α_i is a time-invariant worker component, $\Psi_{J(i,t)}$ a time-variant establishment component, $x_{it}^{'}\beta$ a linear index of time-varying observable characteristics, $\eta_{J(i,t)}$ is a mean zero random match component, ς_{it} is a unit root component of individual wage and ϵ_{it} is a mean zero transitory error.[9] All the error terms go into the same random effects component, r_{it}. α_i will be used as a measure of the individual's ability, while $\Psi_{J(i,t)}$ will be used as a ranking of the firm (high wage paying or low wage paying). Following Card et al. (2013b), α_i can also be interpreted as the portion of the individual's earnings power that is fully portable across employers. It is a combination of skills and other factors that are rewarded equally across employers. $\Psi_{J(i,t)}$ captures the proportional pay premium that is common to all employees at workplace j (i.e., all individuals for whom $J(i,t) = j$). This could be rent sharing, efficiency wage premium or strategic wage posting behavior. For more information on the AKM model, and it's identification, I refer the reader to the Appendix 5.A.1 and to Card et al. (2013b).

[9] The seminal work by Abowd et al. (1999) provides an empirical approach on how to computationally tackle the estimation of the worker and the firm fixed effect with an empirical investigation of France. Haltiwanger et al. (1999) is an example of the application to US data. Up until Abowd et al. (2002) a direct identification of the worker and firm fixed effect was not possible, but based on Abowd et al. (2002) a direct identification is straightforward through the largest connected set. This lead to a vast literature based on the fixed effects. Woodcock (2008) building on Woodcock (2006) added to the discussion by showing that a wage decomposition in the spirit of AKM which fails to control for unobserved worker, firm and match heterogeneity can be misleading. Cardoso (1999) and Card et al. (2013b) are just a few examples of papers that employ AKM to analyze wage inequalities in Portugal and Germany.

5.2.3 Sorting

As briefly mentioned in the introduction, to take the possible matching explanation of the signaling model of GK a step further, matching will be evaluated by different measures. A first impression on sorting is given by the firm fixed effects at the displacement firm and at the re-employment firm. It is an indicator of how the displaced individuals sort themselves into the new firms - as the firm fixed effect represents a ranking of the firms. Furthermore, I will take a look at the correlation of the person and firm fixed effects, as suggested by Abowd et al. (2004). The recent literature by Lopes de Melo (2013), Eeckhout and Kircher (2011), Lentz and Mortensen (2010), to name a few examples, state that one cannot identify the sign of the sorting based on the AKM model. They show that the correlation between the person and the firm fixed effect is biased downwards and therefore mostly zero and may even be negative in some datasets. Due to this bias a distinction between positive assortative matching (PAM) and negative assortative matching (NAM) is not possible.[10]

These papers nevertheless show that the strength of the sorting can be identified, which is arguably the more important measure in economics. Lopes de Melo (2013) shows that the worker-co-worker correlation is a good measure of the strength of the sorting. In his model, the high skilled workers work for the high-productivity firms in the case of PAM (or the low-productivity in the case of NAM). A consequence of this, is that they have high-skill co-workers. Therefore the correlations between their own person effect and the mean co-worker person effect, $\text{Corr}(\theta_i, \tilde{\theta}_{j(i,t)})$, measures the intensity of the sorting in the economy. θ_i denotes the worker fixed effect and $\tilde{\theta}_{j(i,t)}$ is the mean value of θ among the co-workers.

If I assume for the moment that there is PAM in the Austrian data, then the high type workers match with the high type firms.[11] As the goal is to distinguish between signaling and sorting, the relevant stigma arises from the individual layoff, while no such stigma is attached to an individual displaced by a plant closure. In order to see, whether the resulting matching is affected by the "lemon", this chapter takes a closer look at the firm fixed effects, and the different correlation measures as suggested by the literature, before and after the displacement. If the "lemon" plays a role, the difference should be affected; meaning that the difference between pre- and post-

[10]With PAM (NAM), a high skill individual will sort herself into a high (low) productivity firm and a low skilled individual into a low (high) productivity firm.

[11]Please keep in mind that I cannot infer whether there is PAM or NAM without productivity data. This is assumed right now to explain what could possibly happen. Mendes et al. (2010) find for example PAM in Portugal, but they have productivity data and are able to estimate a flexible specification for the productivity.

displacement matching should differ for the closure group and the individual layoff group.

5.3 Data

This chapter uses the Austrian Social Security Database (ASSD) which covers the universe of private sector workers covered by the social security system between 1972 and 2009. The ASSD provides daily information on employment, registered unemployment, total annual earnings paid by each employer, and various individual characteristics of the workers as well as information on employers such as geographical location, industry, and size. For a thorough overview of the data, I refer the reader to Zweimüller et al. (2009).

In the ASSD, the firms are associated with an employer identifier reported in every employment spell of the worker. The current analysis uses only information on male blue and white collar workers in the years 1980-2009. In order to estimate the person and firm fixed effects, I run AKM on a larger sample than the one that is used for inference on sorting and signaling (which only includes displaced individuals).[12] First one main job per year per individual is selected, with a wage and a firm number. If there are overlapping spells, the longest spell is selected as a main spell. To replicate GK a few more restrictions are put on the sample.

In order to use the firm closures as an entry to unemployment, I first create a sample of closing firms. Fink et al. (2010) identify entry and exit of firms using a worker flow approach that follows clusters of workers moving across entities. They also show that their firm definition is comparable to the official firm statistics of Austria.[13] To obtain the individuals affected by a firm closure, firms operating in construction and gastronomy are excluded for seasonality reasons. I only consider male blue and white collar workers who are displaced due to a closure and which comply with the following restrictions. The individual must have been employed in the last quarter of the firm operation, she must have worked at least a year for this firm (to make sure she is unaware of the closure), and her age at displacement must be between 15 and 55 years of age.

To identify mass layoffs, I proceed in a similar fashion. The initial definition is again based on Fink et al. (2010) in the sense that a certain amount of employees is laid off between two quarter

[12]For more information on the AKM sample, see Appendix 5.A.1.
[13]It is secured, that the firm shuts down and it is not just a rename, a spin off or a takeover.

dates. To identify the significant drop, the following assumptions are made: for firms with 11 to 20 employees, the firm size has to decline by at least 6 individuals for it to be counted as a mass layoff. For firms with 21 to 100 employees, the firm size has to decline by 10 individuals in order to be recognized as a mass layoff, while for a firm with more than 100 employees, the firm size needs to decline by 30%.[14] To obtain the individuals affected by a mass layoff, again firms operating in the construction and the gastronomy sector are excluded. The male blue or white collar worker needs to be employed at the mass layoff firm for at least a year, and must have been between 15 and 55 years old at the displacement.[15]

In order to identify an individual layoff I proceed in a different way than for the mass layoffs and the firm closures. First an employment spell has to be identified which is followed by an unemployment spell. If there are less than 28 days between the two spells, then it is defined as a layoff and not a voluntary quit. This is done in similar fashion in e.g., Gruetter and Lalive (2009). The individual layoff sample may be a negatively selected group of individuals since they may have the worst characteristics, but this is the sample needed in order to replicate GK. I have to exclude voluntary quits, since I want to test whether being laid off really signals lesser ability, or whether it may be self-selection. As before the individuals need to have worked for at least a year at the displacement firm and must have been between 15 and 55 at the age of displacement.

Furthermore I only keep those individuals for whom I have a firm fixed effect at the layoff job and at the re-employment job, if the worker finds a new job, and where the worker has a person fixed effect. After this selection the sample contains $98,249$ individual layoffs, $26,461$ mass layoffs and $19,983$ job losses due to a firm closure. Table 5.1 shows the number of job-to-job moves, compared to job-unemployment-job moves and job-unemployment moves. As an example there are no job-to-job moves in the individual layoff group, due to its definition. Overall the displacement sample contains 21.5% of job to job moves, where 12.46% stem from the mass layoffs and the rest from the closures. If the wages on the re-employment firm and on the layoff firm are analyzed 10.01% of the displacement observations are lost. These individuals may drop out of the labor force or remain unemployed or may have found a job outside of Austria at the time of my last observation point. Furthermore, these numbers may be larger than the actual number of individuals, since some individuals may have suffered from multiple layoffs.

[14] These assumptions are standard in the literature, see e.g., Jacobson et al. (1993), Sullivan and von Wachter (2007), von Wachter et al. (2009) who restrict firms to have at least 50 employees and define mass layoff as an instance where the employment of a firm drops by at least 30%.

[15] Seemingly there is no layoff by seniority rule in place for Austria.
https://www.help.gv.at/Portal.Node/hlpd/public/content/201/Seite.2010205.html - accessed 21.02.2014.

The displacement sample contains 8.95% of job short term unemployment (less than 30 days) job moves, 41.87% of job medium term unemployment (between 30 and 365 days) job moves and 17.62% job long term unemployment (more than 365 days) job moves.

Table 5.1: Number of Individuals in the Different Layoff Categories

	All	Layoff	Mass Layoff	Closure
Job to Job	31202	0	18045	12998
Short Term Job	63	0	41	22
Medium Term Job	4918	0	2284	2634
Long Term Job	26221	0	15856	10365
Job Short Term Unemployment Job	12967	10972	841	1154
Short Term Job	101	90	9	2
Medium Term Job	4725	4129	223	373
Long Term Job	8141	6753	609	779
Job Medium Term Unemployment Job	60647	56015	2444	2188
Short Term Job	914	837	54	23
Medium Term Job	29545	27801	959	785
Long Term Job	30188	27377	1431	1380
Job Long Term Unemployment Job	25533	20112	3087	2334
Short Term Job	992	872	82	38
Medium Term Job	11886	9686	1287	913
Long Term Job	12655	9554	1718	1383
Job Unemployment	14503	11150	2044	1309

Source: ASSD, own calculations.

Notes: The term short term unemployment is used when an individual experiences an unemployment spell which lasts less than 30 days. Medium term unemployment is used when the spell lasts between 30 and 365 days, while long term unemployment is used if the spell lasts longer than 365 days. I defined short term job in a similar fashion, meaning that if it lasts for less than 30 days, while it is labelled as a medium term job if it lasts between 30 and 365 days. Jobs that last longer than 365 days are labelled long term jobs.

Table 5.2 displays the summary statistics for the different types of displacement. There are $17,655$ individuals displaced due to a closure, where 27.53% have been displaced around Vienna, 21.13% in eastern Austria, 17.17% in southern Austria, 23.25% in northern Austria and 10.8% in western Austria. Of the displaced individuals due to a closure 30.61% where working in manufacturing, 24.59% in sales and 9.97% in transportation. Of the $23,834$ mass laid off individuals, 46.54% have been displaced around Vienna, 13.52% in eastern Austria, 14.71% in southern Austria, 19.58% in northern Austria and 25.08% in western Austria. 30.55% of these displaced individuals worked in manufacturing, 11.09% in sales and 11.79% in transport. The numbers for the $77,789$ individual layoffs are very similar; 20.39% have been displaced around Vienna, 20.46% in eastern Austria, 23.07% in southern Austria, 23.08% in northern Austria and 10.78% in western Austria. 34.77% of these displaced individuals worked in manufacturing, 23.09% in sales and 8.55% in transport.[16]

Table 5.2: Summary Statistics by Type of Layoff

	Firm Closure		**Mass Layoff**		**Layoff**	
	mean	sd	mean	sd	mean	sd
# Displaced Workers	17655		23834		77789	
# Displaced Workers Region						
Vienna	4862		11093		15858	
East	3731		3223		15919	
South	3033		3507		17945	
North	4105		4668		19508	
West	1908		1329		8387	
# Displaced Workers Industry						
Manufacturing	5402		7278		27038	
Sales	4337		2650		17966	
Transport	1760		2819		6658	
Change in Wages	0.022	0.298	0.024	0.305	-0.002	0.358
Age at Displacement	36.57	9.19	36.65	9.23	34.48	9.14
Ratio of Blue Collar Workers	0.54	0.50	0.45	0.50	0.66	0.47
Tenure at Displacement	1939	1857	2671	2347	1511	1469
Average Firm Operation Duration	4076	3294	9095	4271	8420	4155
Person Effects	3.45	0.24	3.46	0.23	3.41	0.21
Firm Effects	0.05	0.26	0.09	0.24	0.05	0.23
Firm Effects new Firm	0.02	0.28	0.09	0.21	0.02	0.25
Unemployment Duration Since LFP	166	339	144	330	242	397
Age at First Employment	26.61	8.61	25.51	8.07	25.35	8.05
Days Since LFP	3736	2507	4160	2567	3534	2489
Number of Unemployment Spells	2.10	3.75	1.75	3.40	3.22	4.69
Firm Size (*)	15.00	39.22	398.00	5875.02	30.00	1885.23
Total Male Hires	2.57	6.38	78.94	196.33	12.74	69.84
Total Male Fires	5.17	10.93	114.08	221.29	19.14	86.01
Tenure at Disp. Blue Collar	1851	1796	2359	2121	1406	1335
Tenure at Disp. White Collar	1862	1750	2570	2227	1603	1569

Source: ASSD, own calculations.
Notes: (*) For firm size the median is depicted, not the mean. Tenure at displacement, average firm operation duration, unemployment duration since labor force participation (LFP), and days since LFP are measured in days.

A look at the change in wages reveals that it is largest for the mass layoff group 0.024, but very similar to the closure group 0.022. For the individual layoffs, this number differs at -0.002. Looking at the age at displacement the average is about the same for the three groups, 36.6 for the closure group and 36.7 for the mass layoff group while only 34.5 for the individual layoffs. On average the individual layoffs are thus a bit younger than the firm closure or mass laid off sample. Looking at the ratio of blue collar workers in the firm at the displacement date, we see

[16]These percentages do not add up to 100% as for some displaced workers the region is missing, and the percentages for the industry were only calculated for the industries named.

that the share of blue collar workers is higher in firms where we observe more individual layoffs, 0.66, while in the firm closures we observe nearly as many blue collar as white collar workers with a share of 0.54. For the mass layoff firms we observe a share of 0.45 blue collar workers. Looking at the tenure at displacement, we can see that it is smallest for the individual layoffs around 1500 days, which nevertheless equals around 4 years, while for the closing individuals the average tenure at the displacement firm is 1900 days (about 5 years), and for the mass laid off individuals, we observe a longer tenure around 2600 days (about 7 years).

The average firm operating duration shows that the individuals may work at different firm types. The closing firms have the shortest survival at around 4000 days (about 10 years), while individual layoff firms, have an operating duration of 8400 days (about 23 years), while the mass layoff firms have the longest survival at around 9000 days (about 24 years). Looking at the unemployment duration since labor force participation (LFP), we see that the individual layoffs have the highest number of days unemployed with an average of 242 days, whereas it is 166 days for the closure types and 144 days for the mass laid off individuals. The age at first employment is balanced at around 25 years for the three samples. The average days worked since LFP yields a similar picture to the unemployment days. On average the individual layoffs have the shortest days employed with an average of $3,534$ days (nearly 10 years) and around $3,736$ days for the closing sample (about 10 years) and $4,160$ days for the mass layoff sample (about 11 years). The number of unemployment spells is highest for the laid off individuals at 3.2, while it is only 2.1 for the closure types and 1.7 for the mass layoff individuals. In terms of firm size, the closing firms have a median of 15 employees, while the median for the individual layoff firms is 30 and 398 for the mass layoff firms. The total number of male hires and male fires goes along the lines of the firm size. It is highest in the year before displacement for the mass layoff firms, with an average of 78.9 hires and 114 fires, lowest for the closing firms, with an average of 2.5 hires and 5.2 fires, while the individual layoff firms are in the middle of this distribution with around 12.7 hires and 19.1 fires. For completeness the table also includes the means of the person and firm fixed effects, but I will return to these effects later when I discuss the heterogeneity.

5.4 Results

This section discusses the main results. Section 5.4.1 present the estimates of the person and firm fixed effects to test whether or not firms use leeway when deciding whom to lay off.[17] In other words, Section 5.4.1 tests whether the least able are laid off individually and whether individuals suffering from a closure are more heterogeneous. Section 5.4.2 addresses the "lemon" by replicating GK. GK is then taken a step further by differentiating between high ability individuals. Finally Section 5.4.2 addresses whether the "lemon" affects the resulting matching.

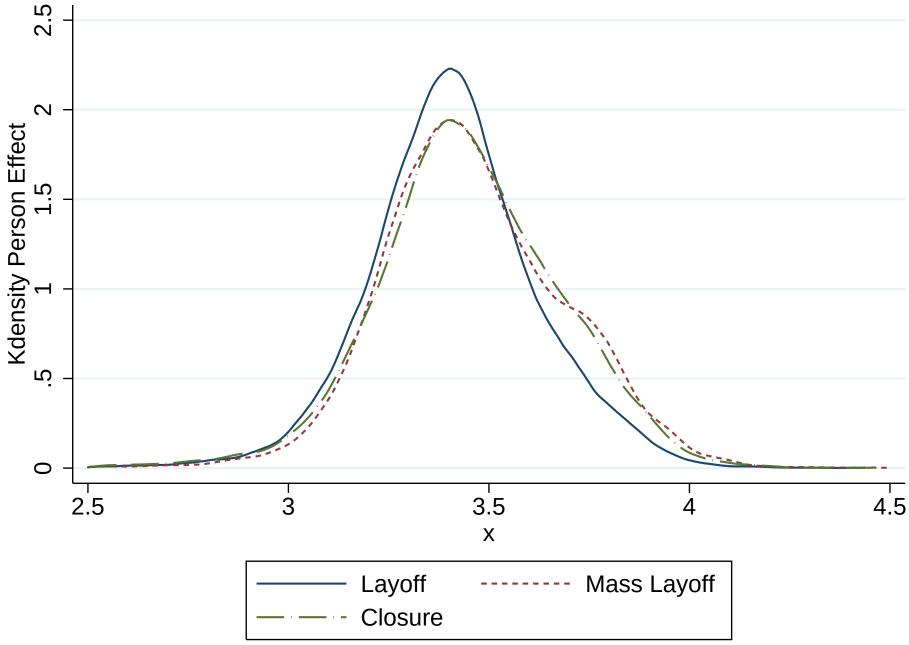
5.4.1 Heterogeneity

Figure 5.3 plots the densities of the estimated person effect for the different layoff types. This graph gives us a first glance whether the underlying assumption, that firms have more leeway in determining whom to layoff in case of a mass layoff and an individual layoff than in a closure event, is true. If it is true that firms layoff the least able individually, we should observe a lower mean for the individual group compared to the closures, whereas the mean for the mass layoffs should be in between the individual layoffs and the closures. Therefore when comparing the mass layoffs with the individual layoffs, we should observe more low productivity individuals in the individual layoff group. Eyeballing, does not allow me to conclude that the distribution of the closure and mass layoff types differ. Nevertheless, the individual layoff is always to the left of the closure and the mass layoff curve. This observation points into the right direction: on average the individually laid off seem to be less able and less heterogeneous than the other types. The Kolmogorov-Smirnov test rejects equality of the distributions.

Table 5.3 takes a closer look at the means and the variances of the person effects across the different groups. The results from the whole AKM file are included in order to get a feeling where the displaced individuals stand compared to the individuals in the connected set. The following relationship between the means of the person effects is observed: mean(mass layoff) = 3.461 > mean(closure) = 3.448 > mean(layoff) = 3.410. These means are significantly different from each other, as the different p-values in Table 5.3 show. On average the individual layoffs are the least able, as expected, but unlike suggested, the mass layoff group seems to be more able than the closing types, at least in our sample. In terms of variance and therefore heterogeneity, the heterogeneity is expected to be highest among the closure types, and lowest among the

[17] The reader is referred to the Appendix 5.A.1 where the validity of the AKM model is discussed. The validity is checked using an event study as in Card et al. (2012b), which allows me to show that the crucial assumptions are fulfilled.

Figure 5.3: Person Effects



individual layoffs. Looking at the data the following relationship holds: Var(closure) = 0.058 > Var(mass layoff) = 0.53 > Var(layoff) = 0.046. The p-values reported in Table 5.3 are from a Levene Test of variance equality and they show that the variances are significantly different from each other.[18] This result supports the conjecture that firms use their knowledge about the workers ability when deciding whom to layoff.[19]

If the sample is split and only white collar workers are analyzed, the following holds: mean(mass layoff) = 3.557 ≈ mean(closure) = 3.556 > mean(layoff) = 3.503. The difference between the mass layoff and the closure group is not significant anymore, but still the individually laid off are on average the least able. For the variances the following holds: Var(closure) = 0.067 > Var(layoff) = 0.061 > Var(mass layoff) = 0.058. A little switch between the mass layoff and the individual layoff group can be observed, but nevertheless the heterogeneity is highest in the closing sample which is as theory would predict. Looking at the blue collar sample we have: mean(mass layoff) = 3.368 > mean(closure) = 3.362 ≈ mean(layoff) = 3.360. The difference between the closure and the individual layoff group is not significant, but the difference between the mass layoff and the individual layoffs is significant, thus on average the individually laid off

[18] The relationship also holds, if a robust version of this test is used. This holds true for all the following Levene tests.

[19] Figure 5.12 in the appendix, shows the same graph as Figure 5.3 but including all individuals, also those that have not been laid off. This graph supports the idea that the least able have been laid off.

are the least able type. In terms of the heterogeneity, I find: Var(closure) = 0.037 > Var(layoff) = 0.032 ≈ Var(mass layoff) = 0.033. Again the closing types are the most heterogeneous while the difference between the mass layoff and the individual layoffs is not significant. These results support the assumption usually made, that firms lay off the least able first.

Table 5.3: Heterogeneity in Layoff Decision? - Person Effect

	PERSON EFFECTS						
	AKM	**CL**	**ML**	**Lay.**	**Two Sided P-value**		
					CL-ML	Layoff-CL	Layoff-ML
Whole sample							
N	3703068	20006	26597	98249			
Mean	3.389	3.448	3.461	3.410	0.000	0.000	0.000
Variance	0.113	0.058	0.053	0.046	0.000	0.000	0.000
White Collar							
N	1692802	8228	12513	32667			
Mean	3.474	3.556	3.557	3.503	0.964	0.000	0.000
Variance	0.124	0.067	0.058	0.061	0.000	0.000	0.001
Blue Collar							
N	2785345	10851	12263	63117			
Mean	3.337	3.362	3.368	3.360	0.024	0.134	0.000
Variance	0.083	0.037	0.033	0.032	0.000	0.000	0.443

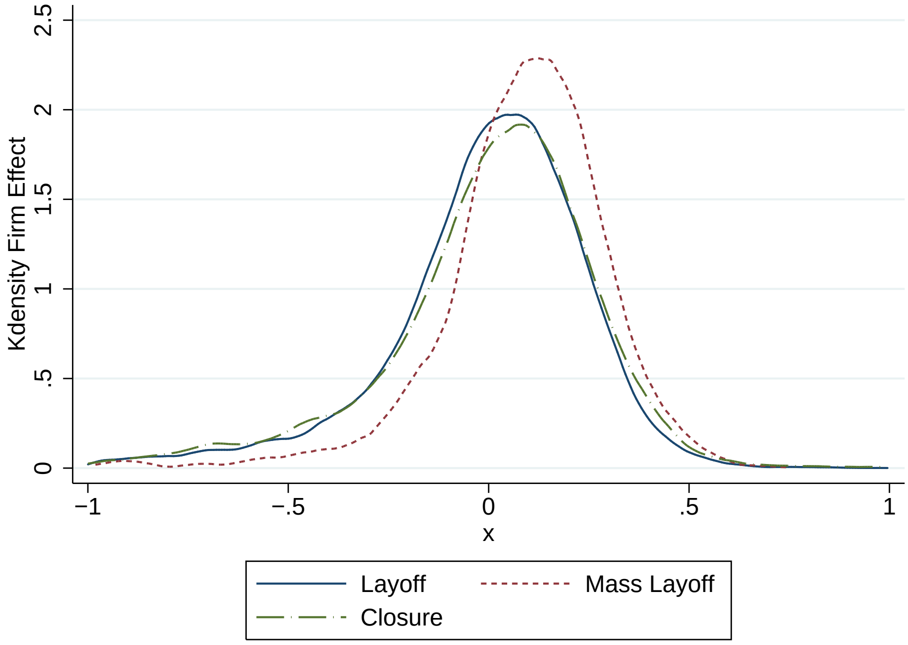
Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample, Lay. = individual layoff sample.

Figure 5.4 takes a different angle by looking at the differences between the firm fixed effects. This should help shed some light on whether really the worst firms shut down, and how different the firms are. The mass layoff curve is always to the right of the other two groups, meaning that on average the mass layoff firms are different from the closure or layoff firms. This finding is in line with the summary statistics. On average the mass layoff firms are different from the closure or individual layoff firms. Looking at the closure and the individual layoff firms, the trend is not as clear. One could try to argue that the curve of the closure group is shifted slightly to the right compared to the mass layoff group which is confirmed by the Kolmogorov-Smirnov test (rejecting equality of the distributions).

Table 5.4 includes the different means and variances of the firm fixed effects. The first panel takes a look at these values at the displacement firm. For the means of the firm fixed effects, the following relationship holds; mean(closure) = 0.043 ≈ mean(layoff) = 0.046 < mean(mass layoff) = 0.098. The mass layoff firms have the highest fixed effect, while the closure firms the lowest - reflecting why they are closing. Mass layoff firms seem to be paying higher wages on average than individual layoff and closing firms. The Levene test concludes that: Var(closure) = 0.070 > Var(layoff) = 0.057 > Var(mass layoff) = 0.056. The closing firms are thus the most diverse, while mass layoff firms are the least variable. These results are confirmed in the first

Figure 5.4: Firm Effects at Displacement



panel of Table 5.5, a sensitivity check, which uses the mean co-worker person effect at the layoff firm instead of using the firm fixed effect.

Table 5.4: Heterogeneity in Layoff Decision? - Firm Effects

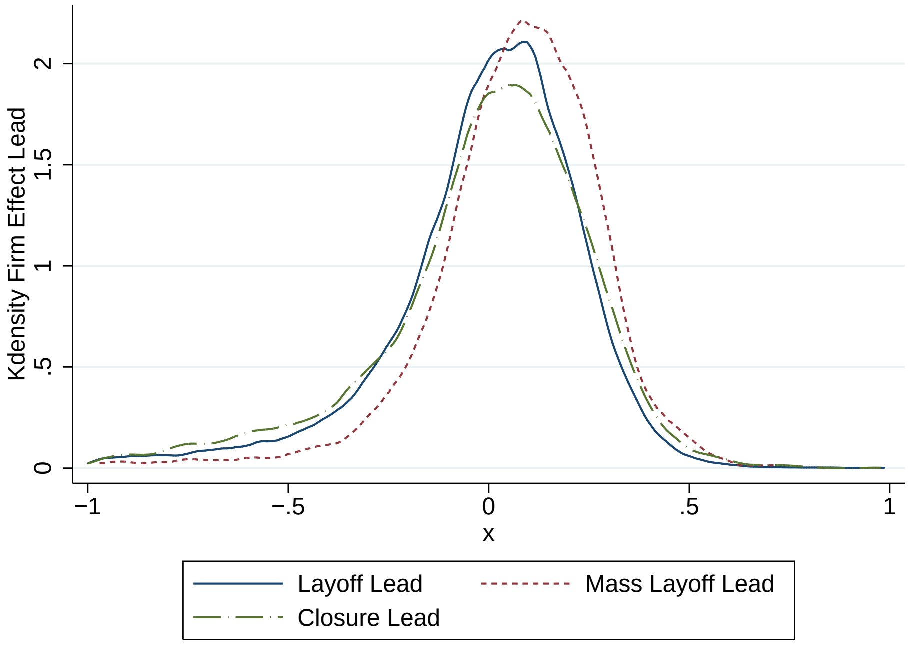
	FIRM EFFECTS				**Two Sided P-value**		
	AKM	**CL**	**ML**	**Lay.**	CL-ML	Lay.-CL	Lay.-ML
			At the Displacement Firm				
Whole sample							
N	3703068	20006	26597	98249			
Mean	0.029	0.043	0.098	0.046	0.000	0.215	0.000
Variance	0.076	0.070	0.056	0.057	0.000	0.000	0.045
			At the Re-employment Firm				
Whole sample							
N		18697	24553	87099			
Mean		0.021	0.090	0.019	0.000	0.333	0.000
Variance		0.076	0.042	0.064	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample, Lay. = individual layoff sample.

Figure 5.5 looks at the differences between the firm fixed effects at the receiving firm. They should capture where the individuals of the different types end up after displacement. If the layoff type did not matter, I would expect similar distributions. Comparing Figures 5.4 and 5.5 we see that the distribution changed, but the mass layoff individuals seem to end up at better firms (on average their curve is furthest to the right). The individual layoffs and the closure individuals seem to end up at slightly better firms than before displacement. Hypothesizing that the closing curve is a bit more to the right than the layoff curve, should be confirmed by tests. The Kolmogorov-Smirnov test rejects equality of the distributions.

Figure 5.5: Firm Effects at the Re-Employment Firm



The second panel of Table 5.4 presents the means and variances at the re-employment firm, where the following relationship holds for the means: mean(mass layoff) = 0.090 > mean(closure) = 0.021 ≈ mean(layoff) = 0.019. The comparison to the means at displacement reveals that mass layoffs end up at firms which still have the highest mean and are thus still the highest paying firms. Things have changed quite considerably for the individual and closure layoffs; the means declined in both cases. Individual layoffs lose more than closures, even though on average they end up at the same firm type.[20] The variances reveal the following: Var(closure) = 0.076 > Var(layoff) = 0.064 > Var(mass layoff) = 0.042. Mass laid off individuals end up at the least diverse firm. Closure individuals end up at more heterogeneous firms compared to individual and mass layoffs. Again the sensitivity check with the mean co-worker person effect in Table 5.5 confirms these results.

[20] I will come back to this result later as well, when sorting is addressed in Section 5.4.2.

Table 5.5: Heterogeneity in Layoff Decision? - Mean Co-Worker PE

	Mean Coworker Person Effect					
	Closure	**Mass Layoff**	**Layoff**	**Two Sided P-value**		
				CL-ML	Layoff-CL	Layoff-ML
			At the Displacement Firm			
Whole sample						
N	20006	26597	98249			
Mean	3.418	3.446	3.432	0.000	0.000	0.000
Variance	0.021	0.012	0.020	0.000	0.000	0.000
			At the Re-emp. Firm			
Whole sample						
N	18697	24553	87099			
Mean	3.434	3.457	3.426	0.000	0.000	0.000
Variance	0.027	0.015	0.018	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: AKM stands for the whole AKM sample, CL = closing sample, ML = mass layoff sample.

5.4.2 Signaling versus Sorting?

Gibbons and Katz (1991) Replication

This section presents the replication of GK, thereby trying to find evidence of signaling for Austria. Table 5.6 replicates Table 3 of GK. Like GK, I find a significantly negative effect on the difference between pre and post layoff wages of an individual layoff compared to a closure (reference group). This result does not change when other covariates or number of displacement fixed effects or industry fixed effects are included.[21] Column (1) in Table 5.6 presents results for the change in wages, Column (2) presents results for the pre-displacement wage and Column (3) presents results for the post-displacement wage on a standard set of worker characteristics, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.[22]

Individual layoffs have about 5% larger wage reductions than workers with the same predisplacement characteristics who were displaced due to a closure. Mass laid off individuals on the contrary seem to have slight wage gains of 0.7% compared to the closures. Column (2) and (3) reveal that the estimate in Column (1) arises from both lower pre- and post-displacement wages for the individually laid off. Separate regressions for the sample of white and blue collar workers show that the larger wage reductions seem to be driven by the white collar workers. Usually fewer white than blue collar jobs are covered by collective bargaining (or unions). White

[21] See Table 5.20 in the appendix, for the different specifications.

[22] The standard set of worker characteristics includes a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since labor force participation (LFP), unemployment duration since LFP, tenure at displacement firm, wage at first employment, number of employment spells and number of unemployment spells.

Table 5.6: Coefficients on Layoff and Mass Layoff Dummy

		Dependent Variable*		
		Wage Change	Predisplacement	Postdisplacement
Sample	N	(1)	(2)	(3)
		Coefficient on Layoff Dummy		
Whole sample	125495	-0.049***	-0.019***	-0.068***
		0.003	0.003	0.003
White collar	45271	-0.091***	-0.028***	-0.119***
		0.006	0.005	0.006
Blue collar	75477	-0.017***	-0.003	-0.020***
		0.004	0.003	0.004
		Coefficient on Mass Layoff Dummy		
Whole sample	125495	0.007*	0.026***	0.033***
		0.004	0.004	0.004
White collar	45271	0.051***	-0.008	0.043***
		0.007	0.006	0.008
Blue collar	75477	-0.030***	0.075***	0.046***
		0.004	0.004	0.005

Source: ASSD, own calculations.
Notes: As reference group the individuals suffering from a firm closure are used. The reported regressions include a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first employment, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.
* Dependent variable: Column 1: log(current wage)- log(previous wage). Column 2: log(previous wage). Column 3: log(current wage)

collar individual layoffs have 9% larger wage reductions than closure individuals, blue collar workers suffer from 1.7% wage reductions. This difference is along the lines of the findings in GK. This finding helps to presume that the degree of discretion over whom to layoff is larger in the white collar sample than in the blue collar sample. Furthermore there may be stricter layoff by seniority rules for blue collar workers than for white collar workers.[23] Overall this evidence points into the direction that a "lemons" effect is in place.

The mass layoff dummy for these two samples shows an interesting feature, white collar individuals have wage increases of 5.1% compared to closures, while the blue collar workers suffer a 3% decrease in wages. Thus the close to zero overall effect is composed of a gain for the white collar workers and a loss for the blue collar workers. This could point into the direction that blue collar laid off workers are evaluated according to an individual layoff, but the signal for a mass layoff is not as strong as being individually laid off. The decomposition into pre- and post-displacement wages shows that at the re-employment firm, both blue and white collar

[23]Table 5.2 shows that there is seemingly no difference between blue and white collar workers when a firm closes, but when we observe a mass layoff or an individual layoff, a longer tenure at displacements is observed for the white collar workers (with much higher standard deviations).

workers earn more than a comparable individual who has suffered from a firm closure.

A further step in the replication of GK, is to check whether the information content of a layoff is higher if the individual had longer tenure at the pre-displacement firm - as the pre-displacement employer was able to evaluate the individual's ability over a longer horizon. Therefore an individual layoff where the worker has a longer pre-displacement tenure contains more information. Table 5.7 replicates Table 4 in GK where the layoff dummy is now replaced by a layoff dummy interacted with high tenure and a layoff dummy interacted with low tenure. Here the exact definition of GK is followed where the low tenure dummy is one if an individual had less than 2 years tenure on the pre-displacement job.

Table 5.7: Interaction of Layoff and ML with Low- and High-Tenure Dummy

		Dependent Variable*		
		Wage Change	Predisplacement	Postdisplacement
Sample	N	(1)	(2)	(3)
		Coefficient on Layoff Dummy		
Whole sample				
Layoff x Low Tenure	125495	-0.036***	-0.035***	-0.071***
		0.003	0.003	0.004
Layoff x High Tenure		-0.056***	-0.010***	-0.067***
		0.003	0.003	0.003
White collar				
Layoff x Low Tenure	45271	-0.079***	-0.053***	-0.131***
		0.007	0.006	0.007
Layoff x High Tenure		-0.098***	-0.015***	-0.113***
		0.006	0.005	0.006
Blue collar				
Layoff x Low Tenure	75477	-0.006	-0.013***	-0.019***
		0.004	0.004	0.004
Layoff x High Tenure		-0.023***	0.002	-0.021***
		0.004	0.003	0.004
		Coefficient on Mass Layoff Dummy		
Whole sample				
ML x Low Tenure	125495	0.016***	-0.020***	-0.004
		0.006	0.005	0.006
ML x High Tenure		0.002	0.045***	0.047***
		0.004	0.004	0.004
White collar				
ML x Low Tenure	45271	0.068***	-0.063***	0.005
		0.010	0.009	0.011
ML x High Tenure		0.044***	0.014**	0.058***
		0.008	0.007	0.008
Blue collar				
ML x Low Tenure	75477	-0.020***	0.048***	0.028***
		0.006	0.006	0.007
ML x High Tenure		-0.035***	0.087***	0.053***
		0.005	0.005	0.005

Source: ASSD, own calculations.
Notes: Low Tenure is a dummy which equals one when there is less than 2 years of tenure on the predisplacement job. High tenure is a dummy which equals one when the individual had at least 2 years of tenure on the predisplacement job.
The reported regressions include a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first employment, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies. ML = Mass Layoff
* Dependent variable: Column 1: log(current wage)- log(previous wage). Column 2: log(previous wage). Column 3: log(current wage)

Comparing the results (Austria vs. GK) there are a few differences which are probably due to the larger sample size, leading to lower standard errors and higher power. GK find a coefficient of -0.011 for the whole sample on the interaction of the layoff dummy with the low tenure dummy which is statistically insignificant and a significant coefficient of -0.054 on the interaction with high tenure. This leads to the claim that their findings are driven by the high tenure individuals. I find a 3.6% significant decrease for the low tenure individual layoffs and a significant 5.6% decrease for the high tenure layoffs. As pointed out, the significance may stem from the fact that my sample is larger including $125,495$ observations, while GK only have $3,427$. Nevertheless my results are in line with theirs in the sense that the "lemons" effect is much stronger for the high tenure individuals. Furthermore the effect is again driven by the significantly lower wages at post-displacement, even though the individual layoffs already have lower wages to begin with. This result is confirmed when looking at the white versus blue collar samples. In fact I find a 9.8% decrease for white collar workers with high tenure and a 2.3% decrease for the blue collar workers with longer tenure. A 7.9% decrease for the white collar workers with lower tenure, while there is no effect for the blue collar workers which have a low tenure. These findings are in line with firms having more discretion over whom to layoff in the white collar sample than in the blue collar sample.

When looking at the mass laid off individuals, I find similar results as before. There is no effect for those individuals who have high tenure, while a 1.6% increase is found for the low tenure individuals. This effect is driven by the significantly lower earnings at the pre-displacement firm, and not by the post-displacement earnings. Splitting the sample into blue and white collar workers, I observe a positive effect for white collar workers, no matter whether they work longer or shorter at the displacement firm. The effect ranges between 4.4 and 6.8%. While for blue collar workers the negative effect persists, and is stronger for the high tenured individuals. This effect ranges between 2.0 and 3.5% and is driven by the significantly lower earnings at the post-displacement firm, even though at the post-displacement firm their earnings are on average still 3 to 5% larger than those of a comparable closure individual.

Table 5.8 investigates whether the sorting explanation can be dismissed for Austria as well. As explained in Section 5.2.1, I will need to find $\gamma_2 > 0$ in Equation (5.2) to reject the sorting model. GK find a significant negative effect on γ_1 the switch industry dummy (large in absolute value), a not significant coefficient on the layoff dummy (δ_1) similar in magnitude to the results before. Furthermore they find a positive coefficient on γ_2, the interaction between the switch industry and layoff dummy.[24] The first column of Table 5.8 presents the baseline results of Column (1) in Table 5.6. Column (2) adds the switch industry information, and unlike GK our significant negative coefficient on the layoff dummy (δ_1), as well as on the industry change dummy (γ_1) and on the interaction between industry change and layoff (γ_2) remains. This evidence does not yet exclude sorting as a possible explanation. The results for the mass layoff sample are similar to the previous findings. The coefficient on the mass layoff dummy stays positive and significant, while the interaction with the industry change is negative, and thus driven by the wage loss due to the industry switch.

Table 5.8: Industry Change, Post Displacement Wage

	(1)	(2)
Mass Layoff	0.0329***	0.0486***
	(0.00408)	(0.00575)
Layoff	-0.0678***	-0.0361***
	(0.00329)	(0.00434)
Industry Change		0.0148***
		(0.00547)
Industry Change * Layoff		-0.0633***
		(0.00606)
Industry Change * Mass Layoff		-0.0322***
		(0.00746)
Year FE	✓	✓
Number of Displacements	✓	✓
Industry FE	✓	✓
Region FE	✓	✓
Observations	125495	124896
R^2	0.420	0.421
Adjusted R^2	0.419	0.420

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses. Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since LFP, employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

Gibbons and Katz (1991) taken a step further

As outlined in Section 5.2.1, I will take GK a step further, by including an indicator whether the person is of high ability or not. Figure 5.6 shows why this distinction may be the potentially more interesting result. Categorizing individuals as high ability if they fall into the highest quintile of

[24]Gibbons and Katz (1991) do not show these results in their paper and therefore I am unable to talk about magnitudes.

the person effect, and as low if they fall into the lowest quintile, we observe that the high ability individual layoffs lose most in terms of their wages. Again year zero is the year of displacement, and during the five years before displacement individual layoffs and closures of high ability had more or less the same wages, but when displacement happens, the individual layoff loses in terms of wages and does not catch up within the next five years. This kink in wages is not visible for the low ability individuals.

Figure 5.6: Mean Wages of Re-employed Individuals by Person Quintile

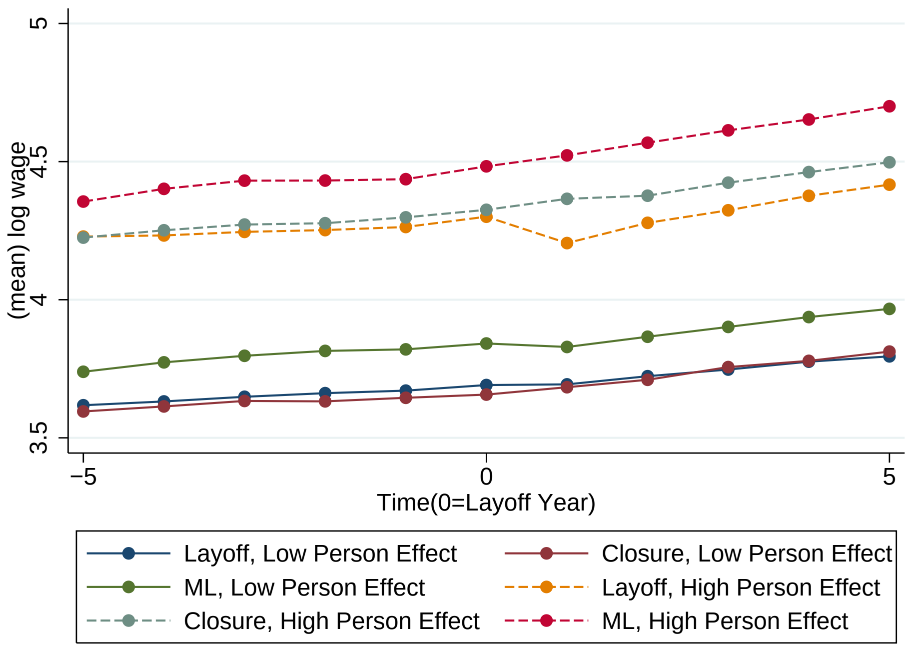


Table 5.9 takes GK a step further by including an indicator of the individual's ability, and an indicator if the layoff firm is a high wage firm (HWF) as outlined in Equation (5.4).[25] This analysis extends GK analysis of the high versus low tenure analysis by trying to see if a high ability individual layoff is able to overcome the "lemon" stigma. Column (1) presents the baseline results from Table 5.6 while Column (2) adds the high ability and HWF indicators. Column (3) includes the additional interaction terms. The coefficient on the individual layoff stays significantly negative. It seems that even controlling for whether or not the individual is of high ability does not suffice to overcome the negative stigma.

[25]The individual's ability is proxied by a dummy which equals one if her person effect falls into the highest quintile, while a HWF is proxied by a dummy equal to one if the firm's fixed effect falls into the highest quintile (similarly defined for the re-employment firm).

Table 5.9: Difference Between Wages High Type Person Effect

	(1)	(2)	(3)
Mass Layoff	0.00666*	0.0139***	0.0205***
	(0.00373)	(0.00366)	(0.00459)
Layoff	-0.0490***	-0.0426***	-0.0338***
	(0.00301)	(0.00294)	(0.00342)
High Person Effect		0.0174***	0.0471***
		(0.00333)	(0.00725)
High Firm Effect		-0.180***	-0.161***
		(0.00305)	(0.00716)
High PE * High FE		0.127***	0.0847***
		(0.00703)	(0.0165)
High Firm Effect at Reemp. Firm		0.208***	0.209***
		(0.00294)	(0.00294)
ML*High PE			-0.0129
			(0.00963)
ML*High FE			-0.0197**
			(0.00897)
ML * High PE * High FE			0.000218
			(0.0206)
Layoff*High PE			-0.0469***
			(0.00829)
Layoff*High FE			-0.0230***
			(0.00771)
Layoff * High PE * High FE			0.0815***
			(0.0193)
Year FE	✓	✓	✓
Number of Displacements	✓	✓	✓
Industry FE	✓	✓	✓
Region FE	✓	✓	✓
Observations	125495	125495	125495
R^2	0.0613	0.1082	0.1086
Adjusted R^2	0.0602	0.1071	0.1075

Source: ASSD, own calculations.
Notes: Dependent variable: log(current wage) - log(previous wage). *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.
Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, unemployment duration since LFP, employment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells and number of unemployment spells.

Table 5.10 presents the different average effects based on Column (3) in Table 5.9. A high ability mass laid off individual has a 5.5% increase in the difference in wages compared to a closure individual. A high ability individual layoff suffers a decrease in wages of about 3.4% compared to a closure individual.[26] Unlike expected, a high ability individual is not able to signal her high ability, and the "lemon" effect still dominates and therefore she still suffers from a wage decline ($\delta_1 + \delta_3 + \delta_4 < 0$). Coming from a HWF decreases the wage, for a mass layoff by about 16% and for an individual layoff by 22%.[27] This large decrease in wages may be due to the fact, that the pre-displacement firm was paying wages that were above the average productivity and this premium is now gone. Another interesting result is that a high ability individual from a HWF, suffers a decrease in wages. A high ability individual can thus not compensate for being previously employed at a HWF, in this case a mass laid off individual suffers a 4.1% decrease, while an individual layoff suffers from a 5.1% decrease.

Table 5.10: Expected Changes in Wages by type

t=	**Mass Layoff**		**Layoff**		
	$\delta_2 + \delta_3 + \delta_5$	P-val.	$\delta_1 + \delta_3 + \delta_4$	P-val.	P-val.
E[Δ W | T = t]	0.0205	0.0000	-0.0338	0.0000	0.0000
E[Δ W | T = t, high PE = 1]	0.0547	0.0000	-0.0336	0.0000	0.0000
E[Δ W | T = t, high FE = 1]	-0.1600	0.0000	-0.2177	0.0000	0.0000
E[Δ W | T = t, high PE = 1, high FE]	-0.0409	0.0001	-0.0512	0.0000	0.4381

Source: ASSD, own calculations.

Notes: These are the expectations calculated from a regression of the change in wages on a mass layoff dummy, a layoff dummy, a high PE dummy, a high FE dummy, the interaction of those two, a dummy for high FE at the reemployment firm, interactions of the high PE and FE with ML and layoff dummies. Furthermore I control for a quadratic in age, age at first employment, firm size, firm operation duration, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, wage at first job, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.

The P-Values on the different coefficients result from an F-test whether they are different from 0 or not. The P-value in the last column on the other hand, is a test of whether the coefficients for the mass layoff group are different from those of the layoff group.

This evidence reinforces the findings of a stigma being attached to an individual layoff. The question which is outside of the GK framework, but that is still interesting, is whether an individual layoff can end up at a high wage firm? Table 5.11 presents the results of a simple logit model (Equation (5.5)) where the dependent variable is one if the individual ends up at a high wage firm.[28]

[26]These numbers are significantly different from each other, and also significantly different from 0. An F-Test on the linear combinations was used to test for significance.

[27]Again these numbers are significantly different from each other and from 0.

[28]I refer the reader for more information on the cell sizes for the different layoff categories to Table 5.19.

Table 5.11: Who Ends up at a High Type Firm?

	(1)	(2)	(3)	(4)
High Firm Effect at Reemp. Firm				
Mass Layoff	0.643***	0.227***	0.329***	0.339***
	(0.0272)	(0.0298)	(0.0472)	(0.0475)
Layoff	-0.0773***	-0.166***	-0.0865**	-0.0250
	(0.0243)	(0.0263)	(0.0375)	(0.0378)
Age	0.0906***	0.0480***	0.0459***	0.0374***
	(0.00761)	(0.00824)	(0.00836)	(0.00842)
Age^2	-0.000454***	-0.000138	-0.000176*	-0.000105
	(0.0000930)	(0.000101)	(0.000102)	(0.000103)
Total Unemployment Duration since LFP	-0.000185***	-0.0000443	-0.0000548	-0.0000778*
	(0.0000425)	(0.0000436)	(0.0000444)	(0.0000446)
Firm Size	-0.0000845***	-0.0000660***	-0.0000201***	-0.0000281***
	(0.00000446)	(0.00000460)	(0.00000550)	(0.00000565)
Firm Operation Duration	-0.000000312	0.0000141***	0.0000153***	0.0000139***
	(0.00000203)	(0.00000218)	(0.00000238)	(0.00000243)
Tenure at Closing Firm	0.0000408***	0.00000434	0.00000365	-0.00000198
	(0.00000545)	(0.00000599)	(0.00000612)	(0.00000618)
Total Employment Duration since LFP	-0.000328***	-0.000240***	-0.000224***	-0.000199***
	(0.0000183)	(0.0000200)	(0.0000207)	(0.0000208)
Wage at First Job	0.0265***	0.0132***	0.0115***	0.0111***
	(0.000637)	(0.000731)	(0.000742)	(0.000746)
Age at First Employment	-0.0705***	-0.0459***	-0.0407***	-0.0392***
	(0.00417)	(0.00458)	(0.00465)	(0.00468)
Number of Unemployment Spells	-0.0533***	-0.0379***	-0.0356***	-0.0288***
	(0.00384)	(0.00396)	(0.00405)	(0.00407)
Number of Employment Spells	0.0922***	0.0598***	0.0575***	0.0519***
	(0.00788)	(0.00856)	(0.00872)	(0.00877)
High Person Effect		0.372***	0.0149	-0.00355
		(0.0299)	(0.0746)	(0.0749)
High Firm Effect		2.222***	2.326***	2.263***
		(0.0189)	(0.0514)	(0.0519)
High PE * High FE		-0.587***	-0.161	-0.159
		(0.0465)	(0.116)	(0.117)
ML*High PE			0.288***	0.329***
			(0.0952)	(0.0956)
ML*High FE			-0.381***	-0.428***
			(0.0664)	(0.0673)
ML * High PE * High FE			-0.0908	-0.0893
			(0.146)	(0.147)
Layoff*High PE			0.300***	0.287***
			(0.0832)	(0.0834)
Layoff*High FE			-0.241***	-0.295***
			(0.0560)	(0.0565)
Layoff * High PE * High FE			-0.646***	-0.617***
			(0.134)	(0.135)
year FE	✓	✓	✓	✓
Region FE	✗	✗	✗	✓
Industry FE	✗	✗	✓	✓
Observations	139449	139449	139447	139445
Pseudo R^2	0.0543	0.1818	0.1958	0.2040

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.

Table 5.12 presents the marginal effects for a mass layoff, or a layoff, compared to the baseline (closure). The standard errors are computed using the delta method and I find that if an individual was part of a mass layoff, she is nearly 5 percentage points more likely to end up at a high wage firm than a closure individual. This effect is negative but insignificant for an individual layoff. A high ability mass laid off individual is nearly 13 percentage points more likely to end up at a high wage firm, whereas an individual layoff is only 4 percentage points more likely. Thus being a high ability individual and having suffered from an individual layoff does not hamper employment at a HWF. This result may point toward exploitation - individual layoffs are hired at HWF more often than closure individuals, but on average earn a lower wage after displacement. On the other hand coming from a HWF, decreases the likelihood of ending up at a high wage firm by 2 percentage points for a mass layoff and an individual layoff. A high ability mass layoff from a HWF is 3 percentage points more likely to end up at a HWF, while an individual HWF layoff is 16 percentage points less likely to end up at a HWF.[29]

Table 5.12: Marignal Effect of Being Employed in a HWF

t=	**Mass Layoff**		**Layoff**	
	ME	σ	ME	σ
P(Emp. HWF = 1 | T = t)	0.0537	0.0106	-0.0032	0.0048
P(Emp. HWF = 1 | T = t, high PE = 1)	0.1333	0.0228	0.0429	0.0138
P(Emp. HWF = 1 | T = t, high FE = 1)	-0.0210	0.0117	-0.0210	0.0112
P(Emp. HWF = 1 | T = t, high PE = 1, high FE)	0.0337	0.0227	-0.1621	0.0241

Source: ASSD, own calculations.
Notes: ME stands for the marginal effect, while σ stands for the standard error, calculated by the delta method.
The marginal effects are calculated at the mean. I ran a logit regression of the probability to be re-employed at a high wage firm controlling for a mass layoff dummy, a layoff dummy, a high PE dummy, a high FE dummy, the interaction of those two, a dummy for high FE at the reemployment firm, interactions of the high PE and FE with ML and layoff dummies. Furthermore I control for a quadratic in age, age at first employment, wage at firt job, employment duration since LFP, unemployment duration since LFP, tenure at the closing firm, number of employment spells, number of unemployment spells, year of displacement dummies, number of displacement dummies, industry dummies and region dummies.

Does the "lemon" affect the resulting matching?

So far I replicated GK results, took them a step further and found slightly more evidence in favor of a signal, but cannot find evidence for rejecting the matching model. Therefore in this section I will investigate other sorting measures as discussed in Section 5.2.3, to see whether the

[29] A related paper which focuses on unemployment durations is Böheim et al. (2011), who find that individuals laid off from a high wage firm take longer to find a job than those coming from a low wage firm (they only analyze the individuals behavior after a plant closure). The main rationale behind their finding is that individuals coming from a high wage firm take longer to update their prior about the wage distribution.

"lemon" also affects the resulting matching.

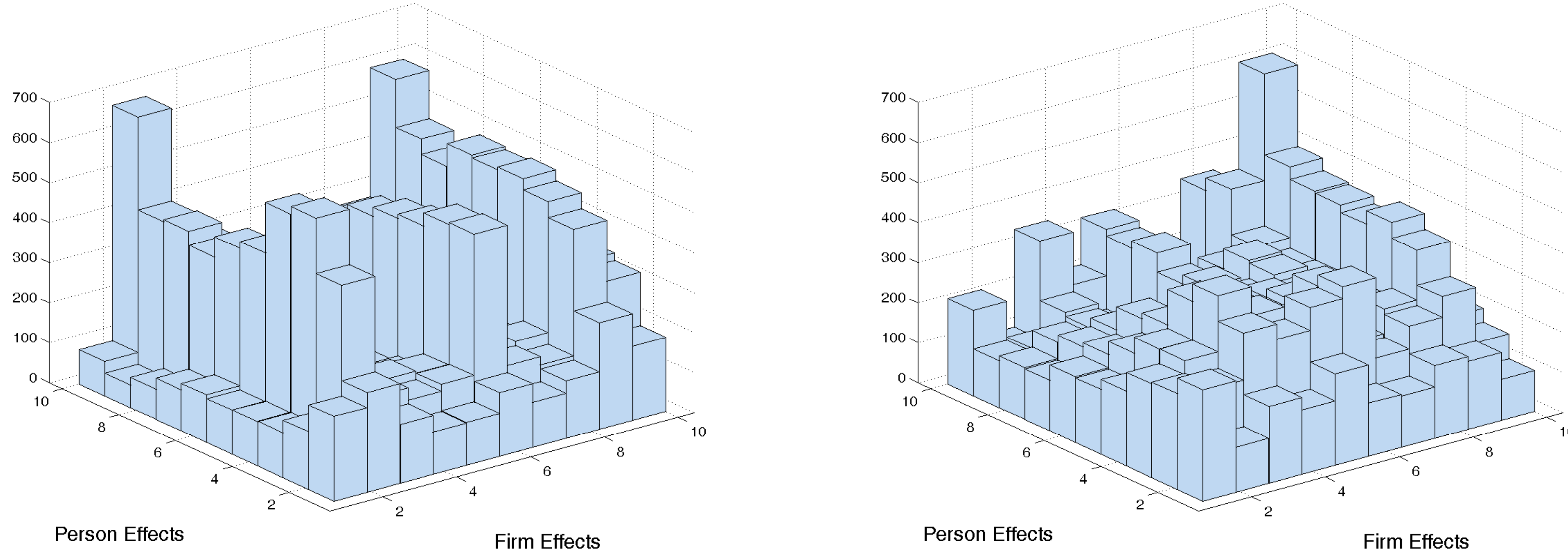
Figures 5.6a, 5.6b, 5.7a, 5.7b, 5.8a and 5.8b plot histograms of the firm and person effects, where the effects are grouped into their respective deciles. These graphs provide some information on who ends up where, and how the sorting in terms of the deciles was before and after displacement.[30] Taking a closer look at Figures 5.6a, 5.6b we see that the correlations of the person and firm effects, even though downward biased increased after the mass layoff. This may indicate sorting before and after the layoff event, as the correlation increases from -0.0023 to 0.1142. Individuals sorted into the second firm decile move, which "evens" the graph out at the re-employment firm. Furthermore there is more mass in the lowest firm decile after displacement, while higher firm deciles seem to remain stable.

Figures 5.7a and 5.7b show the same correlation of the person and firm fixed effects for the closure individuals. The correlation between the deciles of the firm and person effects increases slightly at the new job from a correlation of 0.1046 to 0.1221. Most of the movements seemingly take place in the last firm decile, "evening" themselves out. Again there is sorting before and after displacement.

Figures 5.8a and 5.8b show that the correlation increases slightly after the displacement from 0.0217 to 0.0280 for individual layoffs. The visible movements take place in the first person decile, where individuals move from the lowest firm decile to the highest firm decile. In contrast to the highest person decile, the opposite happens. In these graphs individual movements cannot be observed, only mass changes, which excludes conclusions on which workers moves.

[30] All these graphs use only re-employed individuals, excluding still unemployed individuals.

Figure 5.7: Mass Layoff Deciles

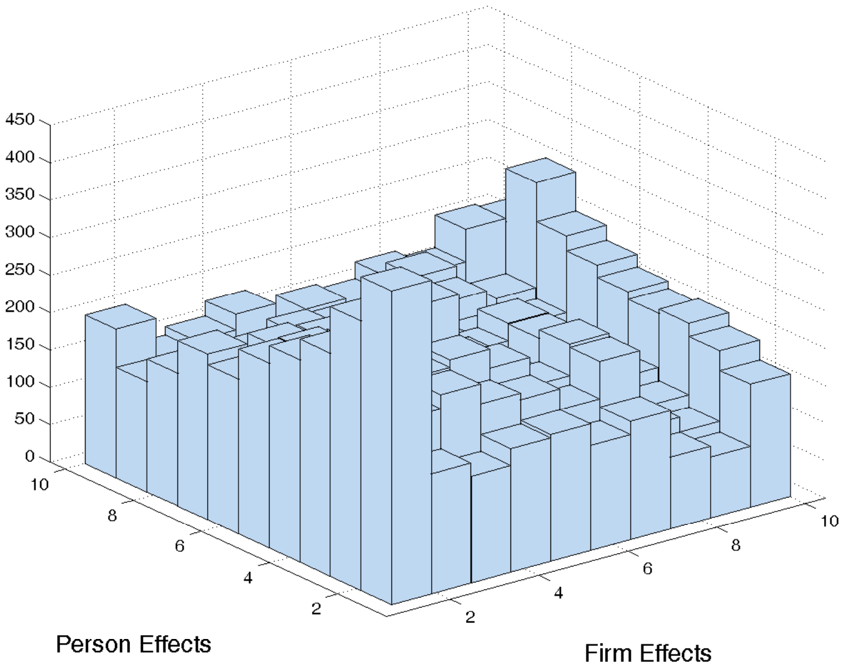


(a) At Layoff Firm Corr(PE,FE)=-0,0023

(b) At Re-Emp. Firm Corr(PE,FE)=0,1142

Figure 5.8: Closure Deciles

(a) CL Deciles at Layoff Firm Corr(PE,FE)=0,1046



(b) CL Deciles at Re-Emp. Firm Corr(PE,FE)=0,1221

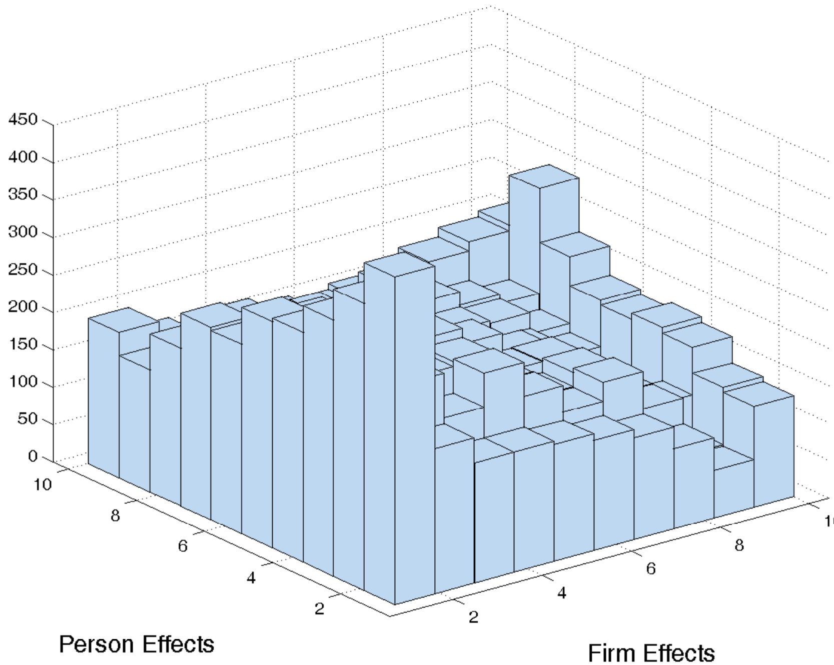
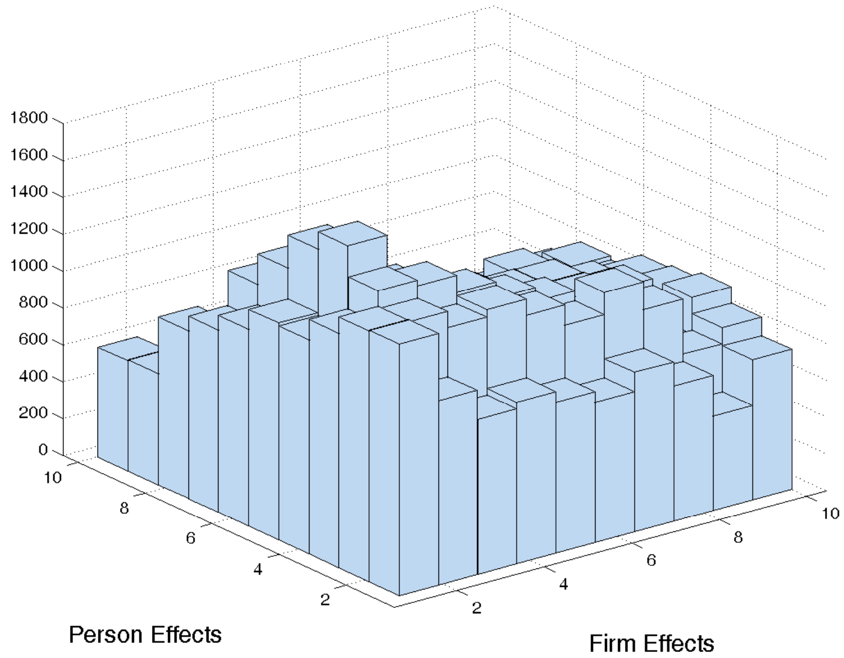
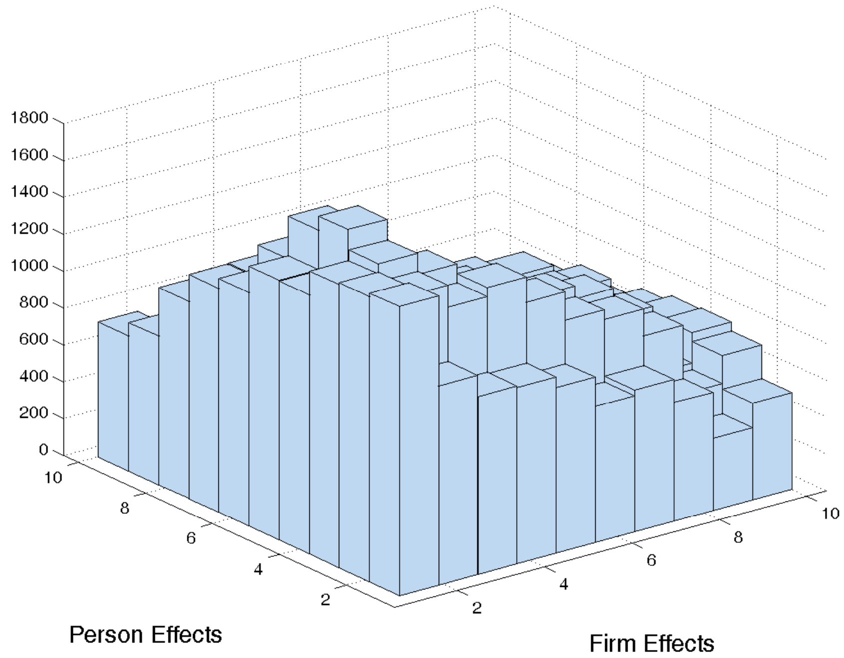


Figure 5.9: Involuntary Layoff Deciles

(a) Layoff Deciles at Layoff Firm Corr(PE,FE)=0,0217



(b) Layoff Deciles at Re-Emp. Firm Corr(PE,FE)=0,0280



The first measure available to check whether the "lemon" affects the resulting matching is the firm fixed effects before and after displacement. Table 5.13 lists the average firm fixed effect for the layoffs at the pre- and post-displacement firm. For the closing individuals, we observe a clear decline of the average firm fixed effect from 0.042 at the pre-displacement firm to 0.021 at the post-displacement firm. Looking at the individual layoffs, the firm fixed effect decreases from 0.046 at the pre-displacement firm to 0.019 at the post-displacement firm. This decrease is larger than the one in the closing firms. This pattern suggests that both sorting and signaling may take place, since the sorting measure decreases more for the individual layoffs than for the closures. Sorting for the mass layoff types remains nearly the same; the average firm fixed effect is at 0.093 before the displacement and 0.090 after the displacement.

These differences remain more or less stable depending on the subsample. The firm fixed effect decreases after the layoff event for the closing and the individual layoffs, for the white collar sample, the high person effect sample, the low person effect sample, the high firm effect, the low firm effect the long firm operation duration and the small turnover sample. In these samples, the firm fixed effect decreases less for the closing types than for the individual layoffs. For the blue collar sample, the short firm operation sample and the high turnover sample the opposite is true. It grows stronger for the layoff sample than for the closing sample (or decreased by less). For the blue collar workers, that might be due to the fact that they are covered by more rigid rules in terms of layoff decisions.

Table 5.14 on the other hand as a sensitivity check, looks at a very similar measure, which focuses on the average co-worker person effect in the pre- and post-displacement firm. Contrary to the firm fixed effect, I find that the measure for the closing types always grows stronger (or declines less) than that of the individual layoff sample, only for the low person effect sample.[31]

For the question of whether or not there is sorting in the data the problems with the correlation between the firm and the person effect have been discussed and whether or not I should use Lopes de Melo (2013)'s measure, which can only identify the strength, but not the sign. Using this measure in Table 5.15, I find that there is significant sorting going on in the case of Austria. Table 5.15 analyzes $\text{Corr}(\theta_i, \tilde{\theta}_{j(i,t)})$ and confirms the differential changes in the sorting measure for the three categories of job loss (mass layoff, individual layoff, and firm closure). This points

[31] In the firm fixed effect changes, the difference between the two has not been significant, so this does not challenge the result from before.

Table 5.13: Sorting Measure: $\Psi_{j(i,t)}$

	Closure		Mass Layoff		Layoff		Two-Sided P-value		
Sample	Mean	P.	Mean	P.	Mean	P.	CL-ML	Lay-CL	Lay-ML
Whole sample									
N	18697		24553		87099				
Predisplacement	0.042	0.000	0.093	0.000	0.046	0.000			
Postdisplacement	0.021	0.000	0.090	0.000	0.019	0.000			
Δ	-0.021	0.000	-0.003	0.027	-0.026	0.000	0.000	0.007	0.000
White Collar									
N	7803		11739		27401				
Predisplacement	0.068	0.000	0.022	0.000	0.055	0.000			
Postdisplacement	0.058	0.000	0.066	0.000	0.011	0.000			
Δ	-0.010	0.000	0.044	0.000	-0.044	0.000	0.000	0.000	0.000
Blue Collar									
N	10018		11035		57494				
Predisplacement	0.018	0.000	0.165	0.000	0.039	0.000			
Postdisplacement	-0.011	0.000	0.114	0.000	0.023	0.000			
Δ	-0.029	0.000	-0.051	0.000	-0.016	0.000	0.000	0.000	0.000
High Person Effect									
N	3139		4610		8343				
Predisplacement	0.066	0.000	0.093	0.000	0.037	0.000			
Postdisplacement	0.054	0.000	0.111	0.000	-0.007	0.063			
Δ	-0.011	0.002	0.018	0.000	-0.044	0.000	0.000	0.000	0.000
Low Person Effect									
N	3689		4473		20037				
Predisplacement	-0.010	0.055	0.076	0.000	0.036	0.000			
Postdisplacement	-0.033	0.000	0.051	0.000	0.011	0.000			
Δ	-0.023	0.000	-0.025	0.000	-0.025	0.000	0.694	0.657	0.983
High Firm Effect									
N	3337		7259		13463				
Predisplacement	0.342	0.000	0.301	0.000	0.321	0.000			
Postdisplacement	0.225	0.000	0.206	0.000	0.158	0.000			
Δ	-0.117	0.000	-0.095	0.000	-0.163	0.000	0.000	0.000	0.000
Low Firm Effect									
N	4496		6014		21560				
Predisplacement	-0.300	0.000	-0.183	0.000	-0.246	0.000			
Postdisplacement	-0.223	0.000	-0.063	0.000	-0.148	0.000			
Δ	0.077	0.000	0.120	0.000	0.098	0.000	0.000	0.000	0.000
Long Firm Operation									
N	199		8465		22522				
Predisplacement	0.038	0.001	0.043	0.000	0.082	0.000			
Postdisplacement	0.009	0.612	0.081	0.000	0.037	0.000			
Δ	-0.029	0.029	0.038	0.000	-0.045	0.000	0.000	0.318	0.000
Short Firm Operation									
N	14750		8139		34133				
Predisplacement	0.037	0.000	0.135	0.000	0.008	0.000			
Postdisplacement	0.018	0.000	0.088	0.000	-0.002	0.135			
Δ	-0.019	0.000	-0.046	0.000	-0.010	0.000	0.000	0.000	0.000
High Turnover									
N	10624		7447		31312				
Predisplacement	0.016	0.000	0.069	0.000	0.024	0.000			
Postdisplacement	-0.003	0.284	0.068	0.000	0.019	0.000			
Δ	-0.019	0.000	-0.000	0.917	-0.005	0.000	0.000	0.000	0.113
Small Turnover									
N	3058		7814		24869				
Predisplacement	0.072	0.000	0.071	0.000	0.051	0.000			
Postdisplacement	0.041	0.000	0.062	0.000	0.009	0.000			
Δ	-0.031	0.000	-0.009	0.000	-0.042	0.000	0.000	0.032	0.000

Source: ASSD, own calculations.

Notes: P. designates the two sided P-value of a t-test whether the mean is equal to zero at the 95 percent level.

High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

Table 5.14: Sorting Measure: $\tilde{\theta}_{j(i,t)}$

Sample	Closure Mean	Closure P.	Mass Layoff Mean	Mass Layoff P.	Layoff Mean	Layoff P.	Two Sided P-value CL-ML	Two Sided P-value Lay-CL	Two Sided P-value Lay-ML
Whole sample									
N	18697		24553		87099				
Predisplacement	3.417	0.000	3.448	0.000	3.432	0.000			
Postdisplacement	3.432	0.000	3.457	0.000	3.426	0.000			
Δ	0.015	0.000	0.009	0.000	-0.006	0.000	0.000	0.000	0.000
White Collar									
N	7803		11739		27401				
Predisplacement	3.468	0.000	3.479	0.000	3.492	0.000			
Postdisplacement	3.484	0.000	3.486	0.000	3.476	0.000			
Δ	0.015	0.000	0.007	0.000	-0.015	0.000	0.000	0.000	0.000
Blue Collar									
N	10018		11035		57494				
Predisplacement	3.376	0.000	3.417	0.000	3.403	0.000			
Postdisplacement	3.391	0.000	3.429	0.000	3.402	0.000			
Δ	0.016	0.000	0.013	0.000	-0.001	0.014	0.037	0.000	0.000
High Person Effect									
N	3139		4610		8343				
Predisplacement	3.534	0.000	3.537	0.000	3.575	0.000			
Postdisplacement	3.577	0.000	3.558	0.000	3.576	0.000			
Δ	0.042	0.000	0.022	0.000	0.001	0.633	0.000	0.000	0.000
Low Person Effect									
N	3689		4473		20037				
Predisplacement	3.309	0.000	3.382	0.000	3.341	0.000			
Postdisplacement	3.297	0.000	3.378	0.000	3.337	0.000			
Δ	-0.013	0.000	-0.004	0.009	-0.004	0.001	0.007	0.001	0.735
High Firm Effect									
N	3337		7259		13463				
Predisplacement	3.440	0.000	3.445	0.000	3.444	0.000			
Postdisplacement	3.454	0.000	3.462	0.000	3.434	0.000			
Δ	0.014	0.000	0.017	0.000	-0.010	0.000	0.100	0.000	0.000
Low Firm Effect									
N	4496		6014		21560				
Predisplacement	3.384	0.000	3.459	0.000	3.416	0.000			
Postdisplacement	3.400	0.000	3.462	0.000	3.419	0.000			
Δ	0.015	0.000	0.003	0.057	0.003	0.002	0.000	0.000	0.494
Long Firm Operation									
N	199		8465		22522				
Predisplacement	3.442	0.000	3.488	0.000	3.446	0.000			
Postdisplacement	3.449	0.000	3.483	0.000	3.434	0.000			
Δ	0.007	0.357	-0.005	0.000	-0.012	0.000	0.051	0.018	0.000
Short Firm Operation									
N	14750		8139		34133				
Predisplacement	3.416	0.000	3.424	0.000	3.417	0.000			
Postdisplacement	3.431	0.000	3.444	0.000	3.418	0.000			
Δ	0.015	0.000	0.020	0.000	0.001	0.271	0.010	0.000	0.000
High Turnover									
N	10624		7447		31312				
Predisplacement	3.395	0.000	3.405	0.000	3.403	0.000			
Postdisplacement	3.415	0.000	3.433	0.000	3.412	0.000			
Δ	0.020	0.000	0.028	0.000	0.009	0.000	0.000	0.000	0.000
Small Turnover									
N	3058		7814		24869				
Predisplacement	3.456	0.000	3.476	0.000	3.453	0.000			
Postdisplacement	3.460	0.000	3.470	0.000	3.435	0.000			
Δ	0.004	0.140	-0.005	0.000	-0.019	0.000	0.000	0.000	0.000

Source: ASSD, own calculations.

Notes: High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

into the direction that there is signaling and sorting happening on aggregate. A finding which should not surprise us, since the resulting outcome on the labor market usually is a combination of signaling and sorting. Future research should focus on developing a model that merges the asymmetric information literature with the sorting literature.

The question about expectations and priors concerning sorting may be raised. To give probable priors for the change in the correlations, I would have to assume that the sorting at the displacement firm is not affected by the displacement. The first problem that needs to be addressed, in this case, is that especially the firm fixed effect of the closing firm, may be affected, since these firms are already the "worst" firms, otherwise they would not shut down. Furthermore, the sorting at the displacement firm may also be the result of signaling and sorting based on previous experiences of the firm and the workers. Nevertheless, I may assume at first that the sorting at the displacement is not affected by the displacement type. Since the question I am trying to answer is whether or not the "lemon" affects the resulting matching, the sorting at the re-employment firm may be affected by the layoff. This leaves two possibilities;

1. the sorting at the re-employment firm is not affected by the displacement type. This gives the prediction that I should observe no change in sorting or a trend in sorting.

2. The sorting at the re-employment firm is affected by the displacement type, then it depends on what type (high or low ability) individual is trying to sort herself. Still assuming that the closing types are the ones that do not suffer from a stigma, we get the following predictions, (see Table 5.16);

for the closing individuals, we should observe no change in the sorting measure, or a trend. For the individual layoffs who are affected by the stigma, we should observe a "better" matching since the low ability individuals will now clearly be seen as low ability and should thus find their match. A high ability individual layoff on the other hand will be seen as low ability, and her match will be distorted, we should thus observe a decrease in efficient matching. Talking about efficiency raises another problem; I know how the sorting changes, but I do not know how good or efficient the sorting was before the displacement, so saying that it should become better is not a precise statement. The problem arises that to the best of my knowledge there is no efficiency measure available for sorting, so future research will need to investigate how to measure efficient matching.

Table 5.15: Sorting Measure: Corr($\theta_i, \tilde{\theta}_{j(i,t)}$)

	Closure		**Mass Layoff**		**Layoff**	
Sample	N	Corr	N	Corr	N	Corr
Whole sample						
Predisplacement	18697	0.684	24553	0.491	87099	0.646
Postdisplacement	18697	0.725	24553	0.553	87099	0.648
Δ		0.041		0.061		0.002
White Collar						
Predisplacement	7803	0.655	11739	0.382	27401	0.612
Postdisplacement	7803	0.714	11739	0.490	27401	0.630
Δ		0.059		0.107		0.018
Blue Collar						
Predisplacement	10018	0.620	11035	0.501	57494	0.613
Postdisplacement	10018	0.668	11035	0.541	57494	0.608
Δ		0.048		0.040		-0.005
Only ML, Closure Firms						
Predisplacement	18697	0.684	24553	0.491	4423	0.449
Postdisplacement	18697	0.725	24553	0.553	4423	0.561
Δ		0.041		0.061		0.113
High Person Effect						
Predisplacement	3139	0.408	4610	0.112	8343	0.440
Postdisplacement	3139	0.430	4610	0.181	8343	0.451
Δ		0.023		0.069		0.011
Low Person Effect						
Predisplacement	3689	0.524	4473	0.131	20037	0.468
Postdisplacement	3689	0.626	4473	0.192	20037	0.447
Δ		0.103		0.061		-0.021
High Firm Effect						
Predisplacement	3337	0.693	7259	0.513	13463	0.648
Postdisplacement	3337	0.723	7259	0.549	13463	0.630
Δ		0.030		0.037		-0.017
Low Firm Effect						
Predisplacement	4496	0.751	6014	0.359	21560	0.777
Postdisplacement	4496	0.792	6014	0.461	21560	0.730
Δ		0.041		0.102		-0.047
High Firm and Person Effect						
Predisplacement	602	0.139	1104	0.007	1423	0.119
Postdisplacement	602	0.117	1104	0.149	1423	0.134
Δ		-0.022		0.141		0.015
Low Firm and Person Effect						
Predisplacement	1151	0.527	1091	0.165	5068	0.544
Postdisplacement	1151	0.643	1091	0.157	5068	0.486
Δ		0.116		-0.008		-0.058
Long Firm Operation						
Predisplacement	199	0.714	8465	0.433	22522	0.497
Postdisplacement	199	0.777	8465	0.497	22522	0.582
Δ		0.062		0.064		0.085
Short Firm Operation						
Predisplacement	14750	0.691	8139	0.515	34133	0.740
Postdisplacement	14750	0.734	8139	0.584	34133	0.686
Δ		0.043		0.068		-0.053
High Turnover						
Predisplacement	10624	0.669	7447	0.484	31312	0.629
Postdisplacement	10624	0.725	7447	0.561	31312	0.635
Δ		0.057		0.077		0.007
Small Turnover						
Predisplacement	3058	0.761	7814	0.355	24869	0.714
Postdisplacement	3058	0.751	7814	0.456	24869	0.678
Δ		-0.010		0.102		-0.036

Source: ASSD, own calculations.

Notes: Δ, denotes the change in the correlations at the postdisplacement firm and the predisplacement firm. High person effect designates the highest quintile, while low person effect designates the lowest quintile. The same logic holds for the high and low firm effects. Large firm size refers to a firm size which falls into the highest tertile, small firm size refers to a firm size which falls into the lowest tertile. The same logic holds for turnover. Long firm operation refers to a firm, who's operation duration falls in the highest tertile, while it is short if it falls in the smallest tertile.

Table 5.16: Priors on Sorting

Displacement	Low Ability	High Ability
Closure	No change in sorting	No change in sorting
Layoff	"better" match	even more distorted
	↑ in "better" matching	↓ "better" in matching

5.5 Conclusion

This chapter answers three related questions in the displacement literature of the labor market and combines two strands of the literature, namely sorting (Becker, 1973) and signaling (Gibbons and Katz, 1991). Analyzing individuals laid off due to a firm closure, a mass layoff or an individual layoff, I first test one of the assumptions usually made in the literature, namely that firms have leeway in determining whom to layoff and thus layoff the least able. Comparing individuals laid off due to plant closures, mass layoffs and individual layoffs, using as an ability proxy the person fixed effect from an Abowd et al. (1999) estimation, I confirm that firms layoff the least able individuals, while individuals laid off due to a plant closure are more heterogeneous than the individual layoffs. Individuals laid off due to a mass layoff are also strategically laid off; in terms of the variance of their ability, they are always in between the individuals suffering from a closure and those suffering from an individual layoff. Standard tests for the validity of the AKM estimation are performed, and I am able to confirm the validity of a linear model in the case of wages, which allowed me to use the person and firm fixed effects to determine whether there is sorting or signaling.

To determine whether a so called "lemons" effect from being individually laid off exists, I replicate Gibbons and Katz (1991). I am not able to reject the hypothesis that individual layoffs contain information about the individual's type, since I confirm GK results on signaling (in line with their asymmetric information model). I even take GK a step further and show that the high ability individual layoffs lose the most in terms of wages. A different result which is also important for future research is that high ability individual layoffs get hired at high wage firms, but on average suffer from a wage loss. This result may be evidence of exploitation of the workers type.

The results cannot reject the asymmetric information model but I can also not reject the assortative matching model (Becker (1973)). I cannot confirm the robustness check done in Gibbons and Katz (1991) to exclude the sorting explanation. Therefore I have to go one step further and analyze the sorting before and after displacement. This leads to a tentative reconciliation of the signaling literature with the sorting literature. I find sorting before the layoff event, as well as sorting after the layoff event (measured by the correlation between the worker and firm fixed effect, the correlation between the worker fixed effect and the mean of the co-workers person effect or by the average firm fixed effect, before and after displacement). I observe a differential change in the sorting measure for the three types of layoffs (closures, individual layoffs and mass layoffs). This leads to the conclusion that there is sorting as well as signaling.

As this chapter brings together two strands of the literature, it highlights the fact that in future research we need to model the labor market as a combination of search and signals. The asymmetric information model of GK is a right start of modeling the signal. The question remains how to include it into a search framework of the Becker type and how to measure sorting efficiently.

5.A AKM Appendix

5.A.1 Measure of Productivity according to Abowd et al. (1999) (AKM)

In order to capture unobserved heterogeneity on the individual and the firm level, I follow the formulation of Abowd et al. (1999), where the log daily wage ω_{it} of individual i in year t can be written as;

$$\begin{aligned}\omega_{it} &= \underbrace{\alpha_i + \Psi_{J(i,t)}}_{\text{Fixed Effects}} + x_{it}^{'}\beta + \underbrace{\eta_{iJ(i,t)} + \varsigma_{it} + \epsilon_{it}}_{\text{Random Effects}} \\ &= \alpha_i + \Psi_{J(i,t)} + x_{it}^{'}\beta + r_{it}\end{aligned} \tag{5.7}$$

the sum of a time-invariant worker component α_i, a time-variant establishment component $\Psi_{J(i,t)}$, a linear index of time-varying observable characteristics $x_{it}^{'}\beta$, a mean zero random match component $\eta_{J(i,t)}$, a unit root component of individual wage ς_{it} and a mean zero transitory error ϵ_{it}. All the error terms go into the same random effects component, r_{it}.[32] Following Card et al. (2013b), α_i can be interpreted as the portion of the individual's earnings power that is fully portable across employers. It is a combination of skills and other factors that are rewarded equally across employers. $\Psi_{J(i,t)}$ captures the proportional pay premium that is common to all employees at workplace j (i.e. all individuals for whom $J(i,t) = j$). This could be rent sharing, efficiency wage premium or strategic wage posting behavior. x_{it} captures changes in the portable component of an individual's earnings power. It includes an unrestricted set of year dummies, quadratic and cubic terms in age. The match effect η_{ij} allows for time-invariant wage premium (or discounts) for individual i at establishment j, relative to the baseline level $\alpha_i + \Psi_j$. This can also be interpreted as an idiosyncratic wage premium. It is the complementarity between the skills of the worker and the needs of the firm. These complementarities arise in models where idiosyncratic productivity components are associated with each potential job match and workers receive some share of the rents from a successful match. It is assumed that the match effect has mean 0. ς_{it} captures the drift in the portable component of the individual's earnings power. It can represent employer learning (about the productivity), unobserved human capital accumulation, health shocks or the arrival of outside offers. The drift component is assumed to have mean 0 but contains a unit root. ϵ_{it} presents any left out mean reverting factors, it is also assumed to have mean 0 for each person in the sample.

[32]For completeness, when estimating this equation, I have N^* person-year observations with N workers and J establishments.

Following Abowd et al. (2002) a linear restriction is used on the firm effects within each "connected" set of firms for the estimation.[33] I refer the reader to Card et al. (2012b) for a closer description of the estimation procedure and the discussion of the threats to validity. We will briefly mention the crucial assumptions here. First there is the standard orthogonality condition between the composite error r_{it} and the time-varying covariates X_{it}. Secondly, the crucial assumption is that, the composite error has to be orthogonal to the matrix of establishment identifiers. It is important to notice, that this does not preclude systematic patterns of job mobility related to α_i and or $\{\Psi_1, \ldots, \Psi_J\}$. Following the argument in Card et al. (2012b), for example, a comparison of the number of job movers in the various cells of Tables 5.17 and 5.18, suggests that workers are more likely to move from low to high wage establishments than to move in the opposite direction. This does not represent a violation of the orthogonality condition between the error and the fixed effects because our fixed effects estimator conditions on the actual sequence of establishments at which each employee is observed. Similarly, higher (or lower) turnover rates among lower productivity workers is fully consistent with this condition, as is the possibility that high skilled workers are more (or less) likely to transition to workplaces with higher wage premiums. Mobility may be related to fixed or time-varying non-wage characteristics of establishments, such as location or recruiting effort. Such mobility helps the identification by expanding the connected set of establishments.

Other threats to the validity of the estimation are first sorting based on η_{ij}. The standard Roy (1951) model sorting changes the interpretation of Ψ_j, depending on the match component, different workers may have different wage premium at any given establishment. If job selection takes place based on the match component, we would expect wage gains for individuals who move from one establishment to another to be different from the wage losses for the individuals who make the opposite transition.[34] Furthermore if the match component is the relevant selection criterion, then a fully saturated model with a dummy for each job should fit the data much better than the additively separate baseline model.

Secondly, if abilities are valued differently at different firms, productive workers will experience a wage growth at their initial employer and are then also more likely to move to higher-wage

[33]The "connected" set of firms is the set of all firms which are linked to each other by moves of individuals between these firms. The direction of the move does not matter in order to identify the "connected" set.

[34]I will show in Section 5.A.1, that the gains associated with transitioning from a low to high co-worker-wage firm is roughly equal to the losses associated with moving in the opposite direction. Moreover, the mean wage differentials for workers who move between firms in the same co-worker wage quartile are close to zero in the time frame from 2002-2009, suggesting that there is no general mobility premium for movers.

firms (and vice-versa for less productive workers). This basically means that the drift in the expected wage predicts firm-to-firm transitions. This will lead to an overstatement of the firm effects.[35]

Thirdly, if fluctuations in the transitory error ϵ_{it} are associated with systematic movements between higher- and lower-wage workplaces. The example given in Card et al. (2012b) is; if ϵ_{it} contains an industry by year component and workers tend to cycle between jobs at higher-wage employers that are relatively sensitive to industry conditions, and jobs at low-wage employers that are more stable. (As noted in discussion of Figures 5.10 and 5.11, there is little evidence that mobility patterns are related to transitory wage fluctuations, suggesting that any correlation between mobility patterns and the ϵ_{it}'s are small.)

In Section 5.A.1, I will show that the identification criteria are met, and therefore I may use the firm fixed effects and the person fixed effects to test for heterogeneity, signaling and sorting. The person effects (which can be interpreted as ability) are then used to determine whether individuals laid off due to a plant closure are more heterogeneous than those laid off individually. The firm fixed effect will allow us to analyze the unobservables on the firm levels between the different groups of the layoff firm, as well as of the receiving firm.

AKM Sample

The AKM sample considers the Austrian universe of male blue and white collar workers from 1980 onwards. I select one main job per year per individual, with a wage and a firm number. If there are overlapping spells, I select the longest spell as a main spell. This sample is used to estimate the person and firm fixed effects, but as outlined above, the effects are only identified within the connected set, which is the set of firms that are linked to each other due to the movement of workers between the firms. It does not matter in which direction the link goes. No further restrictions are put on this sample.[36]

[35]This will also be addressed in Section 5.A.1.

[36]To estimate AKM, I use Card et al. (2012b)'s Matlab code. Originally I have $46,492,753$ person year observations, including $3,732,947$ workers at $624,055$ firms with a mean wage of 3.99 and a variance of 0.2846. When I restrict estimation to the largest connected set, I am left with $46,263,319$ person year observations, representing $3,690,879$ workers at $586,600$ firms with a mean wage of 4.001 and a variance of 0.28095. If we estimate the match effects model of AKM I have a root mean squared error of 0.1579 an R^2 of 0.9336 and an adjusted R^2 of 0.9112.

Validity of the AKM Model

To show that the AKM model actually fits the data and that the orthogonality conditions do not seem to be violated, I follow closely Card et al. (2012b).

To address the first threat to the validity concerning the sorting or as Card et al. (2012b) put it: "people who change workplaces will not necessarily experience systematic wage changes. If, on the other hand, different establishments pay different average wage premiums, then individuals who join a workplace where other workers are highly paid will on average experience a wage gain, while those who join a workplace where others are poorly paid will experience a wage loss", I replicate their event study.

To see whether sorting on wage premium happens in the Austrian Data I ran the event study, where I look at job movers and their co-workers wages at the job before and after the job movement. Figures 5.10 and 5.11 classify the movers according to the quartile of their mean co-worker wage. For clarification, the figures only show the wage profiles for workers leaving quartile 1 and quartile 4 jobs. Tables 5.17 and 5.18 provide a complete listing of mean wages before and after the job change event for each of the 16 cells in the two different time intervals (1990-1997 and 2002-2009). These figures look very similar to Figures 6a and 6b in Card et al. (2012b).

The figures suggest that different mobility groups have different wage levels before and after a move. For example, average wages prior to a move for workers who switch from quartile 4 to quartile 1 jobs are lower than for those who move from quartile 4 to quartile 2 jobs, with similar patterns for the other mobility groups. Within mobility groups there is also strong evidence that moving to a job with higher-paid co-workers raises the own wage. People who start in quartile 1 jobs and move to quartile 1 jobs have relatively constant wages, while those who move to higher quartile jobs experience wage increases. Likewise for people who start in quartile 4 jobs.

An interesting feature of Figures 5.10 and 5.11, is the almost symmetry of the wage losses and gains for those who move between quartile 1 and quartile 4 firms. As shown in Tables 5.17 and 5.18, the gains and losses for other mover categories exhibit a similar degree of symmetry, particularly after adjusting for trend growth in wages. This symmetry suggests that a simple model with additive worker and firm effects may provide a reasonable characterization of the

Figure 5.10: Mean Wages of Job Changers, Classified by Quartile of Mean Wage of Co-Workers at Origin and Destination Firm, 1990-97

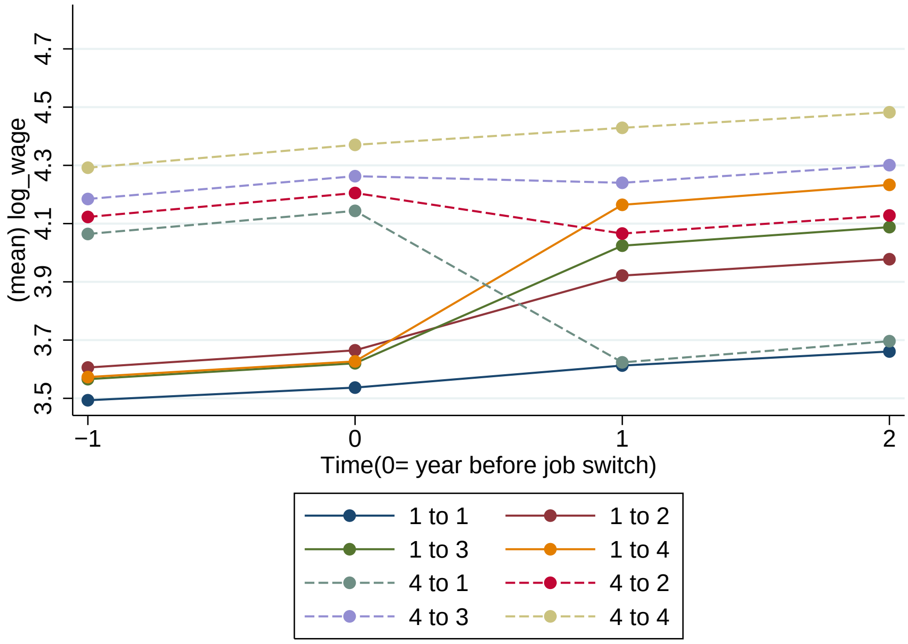
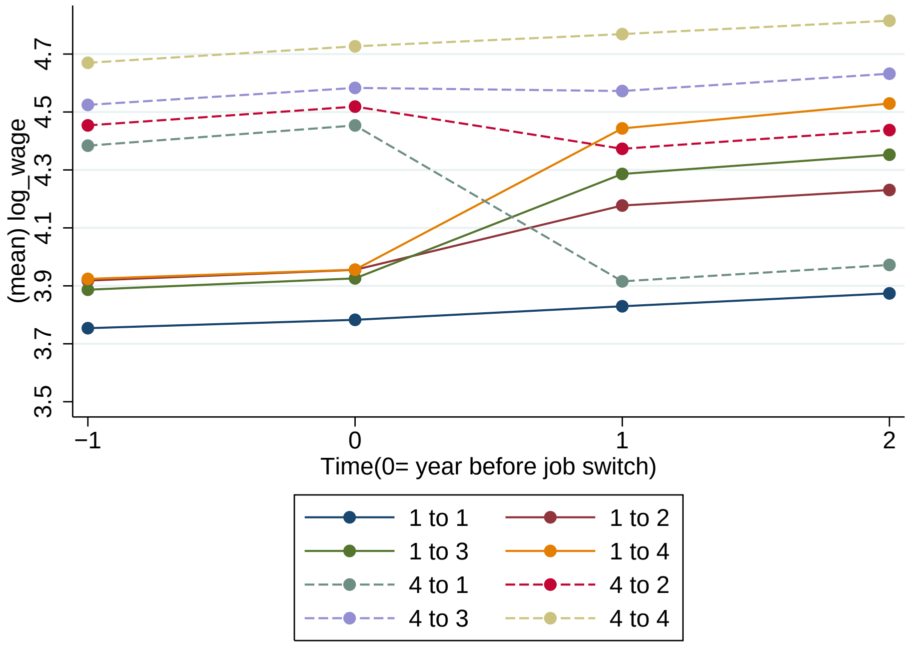


Figure 5.11: Mean Wages of Job Changers, Classified by Quartile of Mean Wage of Co-Workers at Origin and Destination Firm, 2002-2009



mean wages resulting from different pairings of workers to firms.

Table 5.17: Mean Log Wages Before and After Job Change by Quartile of Mean Co-Workers' Wages at Origin and Destination Firms

		Mean Log Wages of Movers				Change from 2 Years Before to 2 Years After	
Origin/Destination Quartile*	Number of Observations (1)	2 Years Before (2)	1 Year Before (3)	1 Year After (4)	2 Years After (5)	Raw (6)	Adjusted** (7)
Years: 2002 - 2009							
1 to 1	63083	3.75	3.78	3.87	3.94	0.19	0.00
1 to 2	30388	3.92	3.96	4.23	4.25	0.33	0.14
1 to 3	16526	3.89	3.93	4.35	4.38	0.49	0.30
1 to 4	9042	3.92	3.96	4.53	4.56	0.63	0.44
2 to 1	27355	4.12	4.17	4.06	4.13	0.01	-0.13
2 to 2	56903	4.22	4.25	4.33	4.36	0.14	0.00
2 to 3	31970	4.24	4.29	4.44	4.47	0.23	0.09
2 to 4	12823	4.24	4.32	4.60	4.63	0.39	0.25
3 to 1	13618	4.24	4.29	4.04	4.13	-0.10	-0.25
3 to 2	23460	4.32	4.36	4.36	4.40	0.08	-0.07
3 to 3	54814	4.40	4.44	4.53	4.55	0.15	0.00
3 to 4	23365	4.46	4.51	4.68	4.71	0.25	0.10
4 to 1	6728	4.38	4.45	3.97	4.07	-0.31	-0.47
4 to 2	8867	4.45	4.52	4.44	4.48	0.03	-0.14
4 to 3	19646	4.52	4.58	4.63	4.67	0.14	-0.02
4 to 4	70615	4.67	4.73	4.82	4.83	0.16	0.00

Source: ASSD, own calculations.
Notes: Entries are mean log real daily wages for job changers who are observed with at least 2 years of data prior to a job change, and two years after. Sample exlcudes mover to/from firms with 1 worker.
* Quartiles are based on mean wages of co-workers at old job in year prior to move, and in new job in year after move.
** Trend-adjusted mean wage change, calculated as mean wage change for origin-destination group, minus mean change for job movers from the same origin quartile who remain in same quartile.

A final important characteristic of the wage profiles in Figures 5.10 and 5.11 is the absence of any Ashenfelter (1978) style transitory dip (or rise) in the wages of movers in the year before moving. The profiles of average daily wages are remarkably flat in the years before and after a move. Taken together with the approximate symmetry of the wage transitions, these flat profiles suggest that the wages of movers may be well-approximated by the combination of a permanent worker component and a firm component, and a time varying residual component that is uncorrelated with mobility.

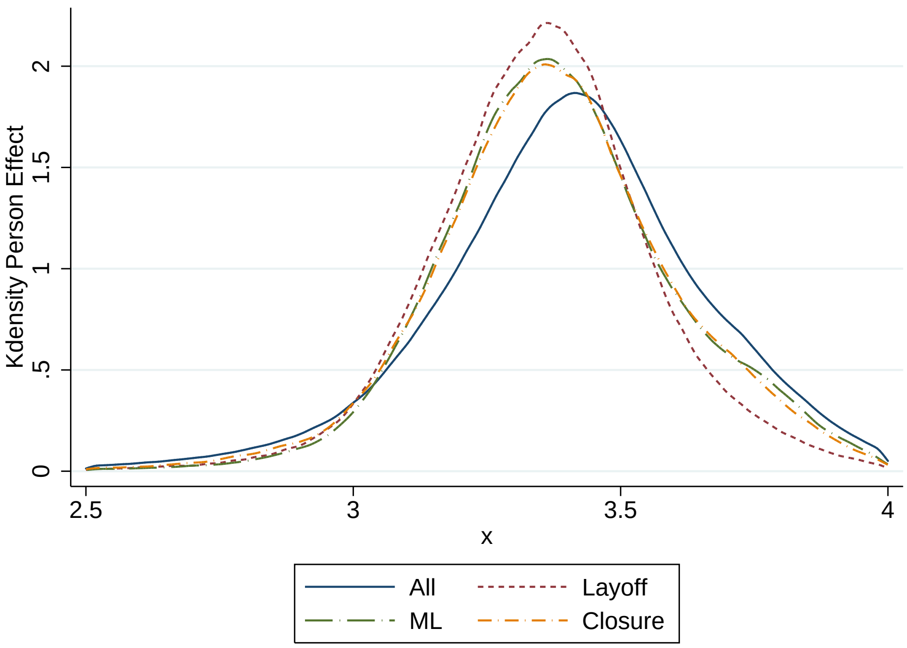
Table 5.18: Mean Log Wages Before and After Job Change by Quartile of Mean Co-Workers' Wages at Origin and Destination Firms

		Mean Log Wages of Movers				Change from 2 Years Before to 2 Years After	
Origin/Destination Quartile*	Number of Observations (1)	2 Years Before (2)	1 Year Before (3)	1 Year After (4)	2 Years After (5)	Raw (6)	Adjusted** (7)
Years: 1990 - 1997							
1 to 1	65459	3.49	3.54	3.66	3.73	0.23	0.00
1 to 2	40251	3.61	3.66	3.98	4.00	0.40	0.16
1 to 3	25297	3.57	3.62	4.09	4.10	0.54	0.30
1 to 4	12528	3.57	3.63	4.23	4.25	0.68	0.44
2 to 1	31417	3.80	3.86	3.77	3.84	0.04	-0.16
2 to 2	44245	3.88	3.94	4.05	4.07	0.20	0.00
2 to 3	33316	3.90	3.96	4.15	4.17	0.27	0.07
2 to 4	15450	3.94	4.02	4.31	4.33	0.39	0.20
3 to 1	18854	3.93	3.98	3.74	3.82	-0.10	-0.28
3 to 2	28421	3.99	4.05	4.07	4.10	0.11	-0.07
3 to 3	47908	4.07	4.13	4.23	4.25	0.18	0.00
3 to 4	29010	4.13	4.19	4.36	4.37	0.25	0.07
4 to 1	10459	4.06	4.14	3.70	3.81	-0.26	-0.47
4 to 2	13368	4.12	4.21	4.13	4.17	0.04	-0.17
4 to 3	23319	4.18	4.26	4.30	4.32	0.14	-0.07
4 to 4	60835	4.29	4.37	4.48	4.50	0.21	0.00

Source: ASSD, own calculations.
Notes: Entries are mean log real daily wages for job changers who are observed with at least 2 years of data prior to a job change, and two years after. Sample exlcudes mover to/from firms with 1 worker.
* Quartiles are based on mean wages of co-workers at old job in year prior to move, and in new job in year after move.
** Trend-adjusted mean wage change, calculated as mean wage change for origin-destination group, minus mean change for job movers from the same origin quartile who remain in same quartile.

5.B Figures

Figure 5.12: Person Effects by Type of Layoff



5.C Tables

Table 5.19: Number of Individuals in the Different PE/FE Categories

	All	Layoff	Mass Layoff	Closure
High Person Effect	18467	10189	4919	3359
High Firm Effect	27240	15775	7916	3549
High Person and Firm Effect	3613	1761	1201	651
Re-emp. at High Firm	19659	11056	5669	2934
Re-emp. at High Firm & High PE	3105	1293	1247	565
Re-emp. at High Firm & High FE	12144	6317	4021	1806
Re-emp. at High Firm & High FE & PE	1588	568	688	332

Source: ASSD, own calculations.

Notes: High person effect if the individual falls into the highest quintile. High firm effect, if the individuals firm falls into the highest quintile of the distribution.

Table 5.20: Difference Between Pre and Post Layoff Wages

	(1)	(2)	(3)	(4)
Mass Layoff	0.00799**	0.00814**	0.00543	0.00666*
	(0.00365)	(0.00365)	(0.00371)	(0.00373)
Layoff	-0.0453***	-0.0460***	-0.0471***	-0.0490***
	(0.00301)	(0.00302)	(0.00300)	(0.00301)
Age	-0.0145***	-0.0146***	-0.0149***	-0.0142***
	(0.000945)	(0.000945)	(0.000941)	(0.000942)
Age^2	0.000134***	0.000136***	0.000133***	0.000127***
	(0.0000116)	(0.0000116)	(0.0000115)	(0.0000115)
Age at First Employment	0.00363***	0.00354***	0.00362***	0.00362***
	(0.000524)	(0.000524)	(0.000521)	(0.000522)
Firm Size	0.00000194***	0.00000198***	-0.00000135***	-0.000000543
	(0.000000376)	(0.000000376)	(0.000000474)	(0.000000485)
Firm Operation Duration	4.37e-08	-6.25e-09	0.000000722***	0.000000282
	(0.000000253)	(0.000000253)	(0.000000268)	(0.000000271)
Total Unemployment Duration since LFP	-0.000000445	-9.00e-08	-0.00000148	-0.000000883
	(0.00000456)	(0.00000456)	(0.00000454)	(0.00000455)
Total Employment Duration since LFP	-0.0000108***	-0.0000118***	-0.00000468*	-0.00000766***
	(0.00000239)	(0.00000239)	(0.00000240)	(0.00000241)
Tenure at Closing Firm	-0.0000107***	-0.0000103***	-0.00000908***	-0.00000888***
	(0.000000715)	(0.000000717)	(0.000000717)	(0.000000717)
Wage at First Job	-0.00260***	-0.00259***	-0.00236***	-0.00229***
	(0.0000825)	(0.0000826)	(0.0000830)	(0.0000832)
Number of Unemployment Spells	0.00158***	0.00144***	0.00133***	0.000844**
	(0.000401)	(0.000401)	(0.000402)	(0.000405)
Number of Employment Spells	0.000541	0.000691	-0.000798	0.000109
	(0.00100)	(0.00100)	(0.001000)	(0.00100)
Year FE	✓	✓	✓	✓
Number of Displacements	✗	✓	✓	✓
Industry FE	✗	✗	✓	✓
Region FE	✗	✗	✗	✓
Observations	125497	125497	125495	125495
R^2	0.040	0.040	0.059	0.061
Adjusted R^2	0.040	0.040	0.058	0.060

Source: ASSD, own calculations.
Note: *,**,*** indicates significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.

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